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A DEA Model to Optimize Insurance Payment Plans based on PACs

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To the Graduate Council:

I am submitting herewith a dissertation written by Gagan Rajpal entitled "A DEA Model to Optimize Insurance Payment Plans based on PACs." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Industrial Engineering.

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Dedication

This dissertation is dedicated to my parents Omparkash Baghi and Kailash Rajpal, my wife Ashdeep Kaur Rajpal, brother Dr.Girish Rajpal, sister-in-law Chinki Rajpal, nephew Brahmya Rajpal, Suvan Rajpal, my dearest niece Saviona Rajpal and rest of my family and my friends, for always believing in me, inspiring me, supporting me and encouraging me, to reach higher in order to achieve my goals.

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Abstract

Healthcare industry has evolved dramatically over the time. From being a “cottage industry” to an “organized industry” has brought lot of changes. The changes have been both good and bad. Among the problems that have surfaced in past couple of decades, rising healthcare cost has been one of the most significant. The rising healthcare cost has been documented to be a symptom of several factors. Since the inception of healthcare as an organized industry several payment models for providers and hospitals have been adopted. Current healthcare reforms have proposed new payments models to curb the rising cost and provide consumer oriented healthcare.

The proposed payment models such as, bundled, capitation, PROMETHEUS, pay-for-performance and traditional model of fee-for-service, all have their merits and demerits. Some are good for chronic and others for acute conditions, some provide bonuses to physicians for high quality and efficient care where as others pay more for number of services used. Our literature review has highlighted the lack of systemic study to analyze the effect of payment models on reimbursement of physicians and hospitals. This study shows that no “single model” can be implemented to serve all the stakeholders. The proposed optimization model is a strategic tool that aligns dynamic patient population with existing reimbursement models and provides information to providers to help them design favorable contracts with insurers. The model also has a potential to help improve planning and operational activities of hospitals.

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List of Abbreviations

ACA – Affordable Care Act
AHRQ – Agency of Healthcare Research & Quality
BATNA – Best Alternatives to Negotiate Agreement
CCR – Charnes Cooper and Rhodes
CMS – Centers for Medicare and Medicaid
CPG – Clinical Practice Guidelines
CPT – Current Procedural Terminology
CRS – Constant Return of Scale
DEA – Data Envelopment Analysis
DMU - Decision Making Unit
DRG - Diagnostic Related Group
ECR – Evidence-informed Case Rates
ECRI – Economic Cycle Research Institute
FFS – Fee-For-Service
GDP – Gross Domestic Product
HCFA – Healthcare Financing Administration
HMO – Health Maintenance Organization
IPPS – Acute Care Hospital Inpatient Prospective Payment System
MAC – Medicare Administration Contractor
MAUT – Multiattribute Utility Theory
MCDA – Multiple Criteria Decision Analysis
MCDM - Multiple Criteria Decision Making
MCDM – Multiple Criterion Decision Making
MOLP – Multiple Objective Linear Programming
PAC – Potentially Avoidable Conditions
PCA – Principal Component Analysis
PPACA – The Patient Protection Affordable Care Act
PPO – Preferred Provider Organization
PPS – Prospective Payment System
RBRVS – Resource Based Relative Value Scale
UCSF – University of California San Francisco
VRP – Variable Return of Scale

CHAPTER 1

INTRODUCTION & PROBLEM STATEMENT

1.1 Background

Introduction of Balanced Budget Act (1997), PL 105-33) brought lot of changes in hospitals in the U.S. The system that was introduced in 1983 promised to bring new ways in which hospitals would get reimbursed. Some of it involved an experimental payment program that waived small rural hospitals from prospective payment system and provided others with incentives for providing treatment to uninsured and those under Medicare. The payment was based on the system of Diagnostic Related Group (DRG) wherein patients with similar conditions are grouped under one group.

Over the last 2 decades the deregulation of hospital pricing and the rise of managed care have led to competition among the stake holders and between the stake holders. Hospitals and insurers negotiate for contracts and these contracts vary significantly across insurers (Alan T. Sorensen, 2001).With the adoption of Prospective Payment System (PPS) in 1983-1984, there have been several evidences to show the insurance companies gaining more in terms of price discounts from the hospitals than vice versa (McNamee, 1995; Loomis, 1994; Phelps, 1992).

“As of July 2010, the United States spent $2.6 trillion per year on healthcare” (Ezekiel J. Emanuel, 2012) which was $2.3 trillion in 2009 (Truffer *et. al.*,. 2010). The rate of growth of spending has been increasing at 2.1% more per year than the growth in Gross Domestic Product

(GDP) for last 30 years. So in last three decades, the percent GDP attributable to healthcare has doubled. If major policy changes are not made, experts predict that this spending will continue to grow. The projections are that by 2040 33.3% of GDP will be spent on healthcare and by 2080 it will increase to 50% (Ezekiel J. Emanuel, 2012).

The growth seems to be partly because of increased Medicaid spending and increase in Medicare payments for providers. Pricewatercooper in its 2002 report concludes that medical advances and consumer demand, government mandate and regulations, and litigation and risk management are the key factors responsible for increase in healthcare cost. Per capita healthcare spending in 2001 grew at 8.7 percent to $5035. According to Levit *et. al.,* (2003), the public funding was more than private funding by 1.2 percentage points in the same year. During the year 2001 hospital spending increased 8.3 percent accounting for 30 percent of the increase in total healthcare spending.

Major contributors for increase in hospital spending were growth in population, price and also per capita increase in quantity of services consumed (Levit *et. al.,* 2003). Further analysis showed that population growth contributed only 0.9 percent, whereas quantities of services used per capita increased by 4.2 percent up from 2.2 percent in 2000, which was the single major contributor of increased hospital spending in 2001, followed by hospital specific inflation rise at 3.2 percent.

A large portion of healthcare expenditures that includes an increase in per capita utilization of hospital services, are spent on waste and defective care (Schoen *et. al.,* 2006), which includes medical errors, and avoidable hospitalizations that cause patients to incur unnecessary services. As per recent report from the Agency of Healthcare Research and Quality (AHRQ) the cost of potentially preventable hospitalizations in 2006 was $30.8 billion. According to Jiang *et. al.,* (2006), 20% of Medicare admissions were due to preventable patient conditions. In another study Jencks *et. al.,* (2009) found that “almost 19.6 % of Medicare patients incurred re-hospitalization with 30 days of their discharge”.

According to Weissman *et. al.,* (1992) and Billings *et. al.,* (1993) panels that compared administrative records with full hospital charts and clinical experience have defined sets of preventable admissions. A group of researchers from UCSF (University of California - San Francisco)-Stanford Evidence Based Practice Center (2002) used scientific literature and validation method to arrive at narrow set of hospital admissions with Prevention Quality Indicator (PQI) conditions that include conditions such as asthma, bacterial pneumonia, hypertension etc. According to de Brantes François *et. al.,* (2010), “as much as 22% of the healthcare expenditure is related to potentially avoidable complications such as hospital admissions for patients with diabetes, ketoacidosis, amputation of gangrenous limbs, congestive heart failure. Reducing avoidable complications by 10% could save $40 billion per year”.

The Centers for Medicare and Medicaid Services (CMS) have started addressing these issues by removing payment adjustments that previously compensated hospitals for certain hospital-acquired conditions (ECRI Institute 2008). Following their footsteps, private insurers have adopted approach in the form of different reimbursement models to remove financial incentives to practices that essentially lead to complications. This places accountability on all stakeholders in the healthcare system.

The three stake holders in the healthcare system are healthcare insurers, healthcare providers (hospitals, physicians etc.) and the patients. The interaction between the three is governed by a contract. Contract means there is an agreement wherein healthcare provider promises to deliver the service to the set of people being covered and in turn is reimbursed by the insurer according to agree upon conditions. Medicare and Medicaid are federal programs which pay for the services provided to elderly, disabled, and low-income patients respectively. Services to rest of the population are provided based on their coverage through private insurers. According to the Federal Centers for Medicare and Medicaid Services, almost 81 percent of the revenue generated by provider is through CMS.

Since the introduction of Balanced Budget Act, the system where hospital and insurer negotiate payment has become operationally competitive mechanism. Prior to this hospitals would set their own prices and insurer would pay full payment for services. This model did not require any kind of competition among third party insurers. Over the last 2 decades the deregulation of hospital pricing and the rise of managed care have led to competition among the stake holders and between these entities. There is a wide level of variation in the contracts negotiated between service providers and insurers (Alan T. Sorensen, 2001).

According to Laffont and Martimort (2001), principle-agent framework is the model that is usually followed to design the healthcare payment systems. The interactions between the insurer and provider are where an insurer (a principle) provides instructions and guidelines for providing patients' medical services to a provider (an agent). It is the insurer's responsibility to formulate a contract that incentivizes patient's prospective health. These incentives provide the motivation towards best practices applied towards well-being of patient.

In the United States people are either insured by private commercial insurers or their government counterparts like Medicare and Medicaid or are uninsured. The coverage is taken either directly or indirectly and is generally bought through a sponsor. Sponsors in turn write different contracts with healthcare insurers wherein they can either buy partial or full coverage as prescribed in their coverage plan. Healthcare insurers in turn write different contract(s), essentially buying services of healthcare providers and pay them as per the design of the contract (Born *et. al.,*, 2004) as explained in Figure 1.1.

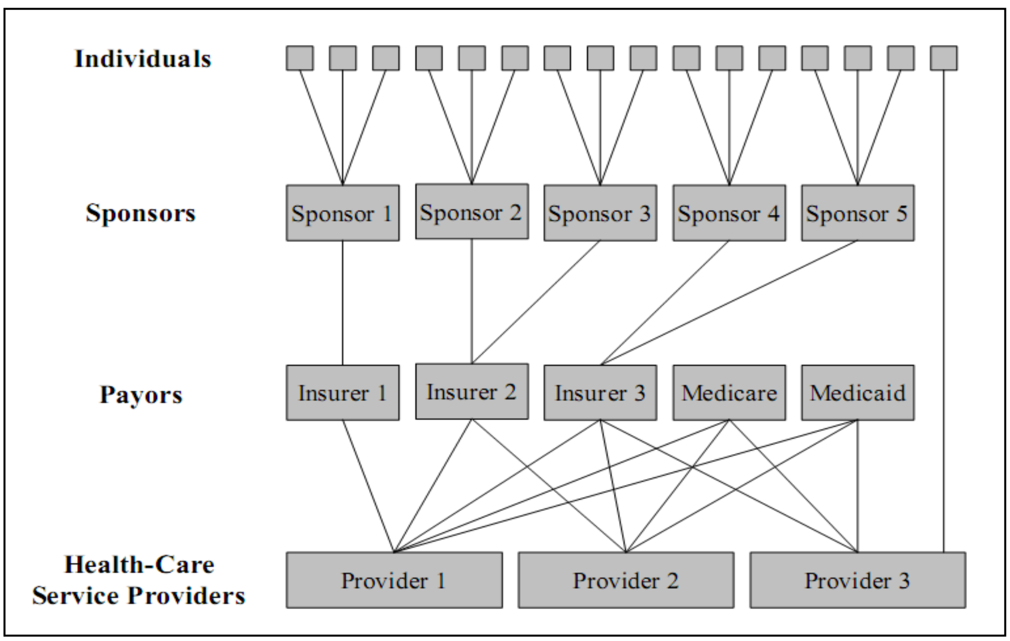


Figure 1.1: Design of healthcare contract (Source: Contract Optimization at Texas Children's Hospital. Interfaces, 2004)

Insurer writes a specific contract with each provider in the network who is generally paid based on per unit of care which could be either per DRG or per inpatient day. The contracts are provider specific and negotiated annually. This also varies across insurers for given providers (Ho, 2009).

The selective nature of contracts is intended to control costs and insurers prefer to contract with hospitals that provide quality care to patients. The drawback of managed care system which started with the enactment of the Health Maintenance Organization Act of 1973, is that the selective nature of contracts also give power to insurers to exclude providers from their network thus negotiating for lower provider price (Brooks *et. al.*,, 1997).

"It is known that healthcare providers have some say for the rates provided by Medicare and Medicaid. There is not much in literature about the bargaining process that goes on between the provider and insurer. According to Ho (2009), there are several stages in the process to design a contract between insurer and a provider":

Stage 1: Hospital makes price offer to contracts.

Stage 2: Contracts choose their hospital networks.

Stage 3: Contracts set premiums.

Stage 4: Consumers and employers jointly choose contracts.

Stage 5: Stick consumers visit hospitals; contracts pay per service provided.

After conducting several interviews with insurers and providers, Ho concluded that providers with high patient satisfaction rate are in a position to demand higher rate of reimbursement. Provider seeks to increase revenue and therefore tend to contract with insurers offering better prices and preferred patients. Despite all the posturing by providers, the leverage is generally skewed towards insurers.

There are several reimbursement plans/models proposed. Some of them have been in use for a long time but never got prominence and others have been proposed recently after recent changes in healthcare policy. The common focus in all the models is quality, and/or efficiency of care provided to the patients in the process of care (Massachusetts Medical Society, 2008). According to the report, making healthcare more efficient would be in terms of rate of utilization of services, such as, radiology, utilization of emergency department; overall expenditures, or medical errors.

This paradigm shift in healthcare policy has radically affected the modes by which stake holders involved in healthcare get benefited, such as hospitals, physicians, patients etc. Different reimbursement models solve the cost Vs. quality differently. As can be seen in Figure 1.2 there is no standard or one particular solution to the situation.

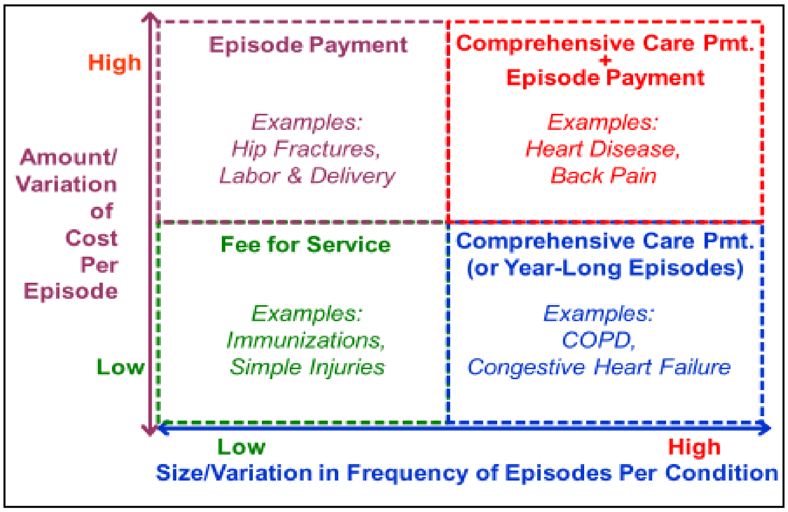


Figure 1.2: Cost Vs quality and reimbursement models (Source: Which Healthcare Payment System is Best?, CHQPR)

1.2 Reimbursement Models

1.2.1 Fee-For-Service

Fee for service as the name suggests means insurer pays for services rendered by the provider based on Clinical Practice Guideline (CPG). The price of the services is established by negotiation between insurer and provider. Charges for all the services that a provider provides are generally listed on their fee schedule, which is based on set of 5 digit codes called Current Procedural Terminology (CPT).

In an ideal world it could be a good model for reimbursing providers, however for the most part it is the insurer who makes a decision of how much each service should be paid and hence the provider feels underpaid. On the other hand there is equally high likelihood of over utilization of services and the model is more prone to be volume driven than value driven. Although this model has weaknesses, it is still the most common methods of reimbursing providers.

1.2.2 PROMETHEUS

PROMETHEUS which stands for Provider Payment Reform for Outcomes Margins Evidence Transparency Hassle-reduction Excellence Understandability and Sustainability was result of a joint effort of a team composed of insurers and providers (Massachusetts Medical Society, 2008). This model is a modification for fee-for-service payment model. The physicians are paid for fee for service, but also receive high bonuses for providing uncomplicated and efficient care to the patients (described in detail in chapter 2).

The model is arguably the most advanced payment reimbursement model currently available. The model is based on Clinical Practice Guidelines (CPGs). CPGs include guidelines for the process and resources required to treat a specific condition (Massachusetts Medical Society, 2008).

1.2.3 Bundled Payment

This is also called as “episode of care” or “case rate” payment. This means a single bundled payment made for a specific condition such as knee replacement or kidney transplant etc. The episode could include different specialists, different facilities, post-operative care etc. involved in an “episode”. The payment is typically made to the hospitals, which divide it among providers involved in the care. In case the total cost of care is less than the bundled payment, the profit is shared among all. Similarly loss is shared among all in case the cost exceeds the bundled payment. This kind of model is appropriate for acute cases such as heart attack, the conditions that have clear beginning and an end (Congressional Budget Office, 2008). In such a condition, under this model a single payment would be made to the provider.

Although this model has drawbacks, the model works better than global payment model in certain cases, such as, acute conditions or different acute episodes of chronic conditions. The difference between “episode of care” or bundled payment model is that risk is shared by both insurers and physicians (Massachusetts Medical Society, 2008).

According to a report, *The Medicare bundled payments for care improvement initiative: An analysis and its implications to potential participants (2011),* there are four different types of bundled payment models based on whether the patient is being treated for an acute or chronic condition. They are –

Model 1: Retrospective Acute Care Hospital Stay Care. This payment model involves only acute-care inpatient hospitalization. The episode of care begins with patient’s hospitalization and ends with his/her discharge.

Model 2: Retrospective Acute Care Hospital Stay Plus post-Acute Care. This model includes acute-care hospitalization and post-acute care following and associated with acute-care episode. Post-acute care can have two options, with option 1 the episode ends before 90 days of and in option 2 the episode ends after 90 days of hospital discharge.

Model 3: Retrospective Post-Acute Care Only. The payment in this model is limited to the episode of only post-acute care following an inpatient hospital stay. It begins with the services provided at skilled nursing home, long-term care hospital etc. 30 days after patient discharge.

Model 4: Prospective Acute Care Hospital Stay Only. This model is like Model 1 wherein, the episode of care starts with patient's hospitalization. And the episode ends upon discharge from the acute care hospital and includes all Part A and Part B services provided during patient's stay.

Table 1.1 below summarizes the reimbursement models, their method of reimbursement, their benefits and concerns.

Table 1.1: Summary, benefits and concerns of Bundled and PROMETHEUS payment models

Model Name	Summary	Method of payment	Benefits	Concerns	Other Comments
Bundled Payments or Episode of care or Case rate payment	Payment covers particular episode of care, such as myocardial infarction or a hip replacement	A bundled payment is made to a hospital, which divides the payment between the hospital and all of the providers who cared for the patient	Hopefully it will give providers a great incentive to coordinate care, thus improving outcomes and reducing waste and unnecessary care	Physicians worry that hospitals will get lion's share and those not affiliated with hospitals or network will find it difficult to participate	How to divide the money fairly?
	Multiple Providers in multiple settings may share in the payment for a patient's episode of care	Doctors and hospital share the differences, whether it is profit or loss		Very sick patients might get shunned as they are very expensive to be treated	How do you prevent providers from being biased and cherry picking patients with good prognosis etc.?
	An episode of care could encompass a period of hospitalization, hospitalization + post-acute case, or a defined time frame of care for a chronic condition			Access to specialist could be limited and defining "episode of care" can be difficult for certain illnesses and chronic conditions	How to define "episode of care"?
PROMETHEUS Payment	it rewards physicians for practicing efficiently and avoiding complications	Physicians are paid fee for service, which is a debit against the case rate	Physicians stand to receive bonuses for high quality, efficient care without being at financial risk	Physicians need the infrastructure to make this model work	It's strength is that it promotes clinical collaboration and coordination of care across specialties and settings of care
	teams negotiate all-inclusive case rates according to evidence-based guidelines for episodes of acute and long term care	Physicians can share a withhold if their team prevents avoidable complications			It's success depends on whether its incentives will follow evidence-based guidelines will enough waste to fund quality-based bonuses for physicians

1.3 Problem Statement

Almost two thirds of Americans have health insurance plan of one form or other highlighting the importance of understanding the competitive interaction between insurers and providers (Quinn, 1998). Competition is not only between insurers and providers but also within insurers and providers. The research done in the past e.g., Pauly (1987, 1988a, 1988b), Staten *et. al.,,* (1987, 1988) and Melnich *et. al.,,* (1992), shows there is a significant correlation between competition and prices in market. The insurance reimbursement plans play a very important role (Burns and Wholey, 1992). Negotiating the terms of reimbursement in contract depends significantly on market power helped by the stake holders.

“The maximum revenue generated from a hospital’s perspective comes from the contract terms established by them with private insurers. The number of contract portfolio maintained by the provider or healthcare provider system can range anywhere from 50 up to 200 with different revenues. With so much revenue at stake, it becomes important to design a contract in such a way that it gets maximized. Reimbursement contract in no ways guarantees the number of patients, but the rate of reimbursement for the service provided” (Born, 2004).

To improve accountability in the delivery of healthcare, Medicare & Medicaid and private insurers have developed several reimbursement plans/models as mentioned above. These models are based on “Evidence-informed Case Rates (ECRs) which is a single, risk-adjusted, prospective or retrospective, payment given to providers across inpatient and outpatient settings to care for a patient diagnosed with a specific condition. Payment amounts are based on the resources required to provide care as recommended in well-accepted clinical guidelines” (de

Brantes, F., 2007). The common denominator for all the ECRs is the window of time period during which any relevant (whether typical or Potentially Avoidable Condition (PAC)) readmission of patient will be reimbursed. The window of time period varies with the model of reimbursement as shown in Figure 1.3.

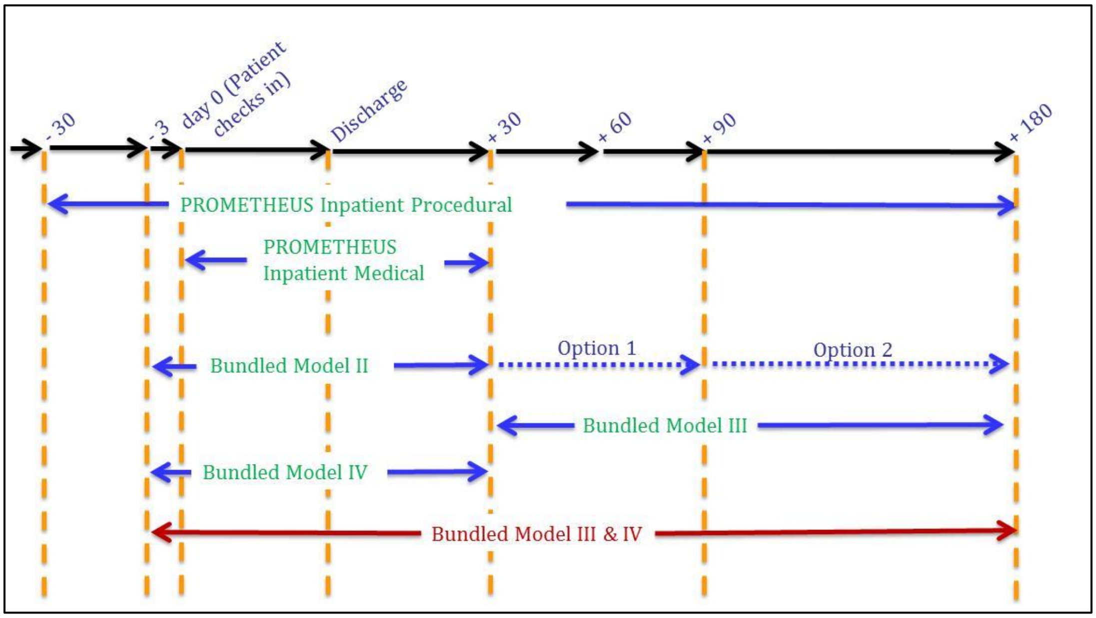


Figure 1.3: Depiction of number of days covered under each reimbursement model

Designing a contract that maximizes patient's health outcomes while allowing the other two stake holders to optimize their own objective functions depend on several factors including reimbursements provided by insurer to the provider. Reimbursement is a complex process that involves many factors not only related to patients' condition but also different cost structures providers have.

All the reimbursement models, considered in the research, provide a chance for both insurers as well as providers to share the savings and thus increasing their revenue by reducing or preventing PACs. The purpose of the research is to design an optimization model, using all the reimbursement models, to maximize the revenue. The optimization model aligns dynamic patient population with existing reimbursement models and provides information to providers to help them design not only favorable contracts with insurers but also help improve their planning and operational activities. The model will also help in hospitals in strategizing their revenues through reimbursements.

1.4 Research Justification

The Patient Protection and Affordable Care Act (PPACA), popularly known as Obama care or Affordable Care Act (ACA), was signed into law on March 23, 2010. The law aims at improving the quality and increasing the affordability of health insurance. The law also aims to reduce escalating healthcare costs and improve healthcare outcomes by moving from current quantity driven system to more quality driven system. This can be achieved by increasing competition, regulation, and incentives to streamline the delivery of healthcare. The changes enacted include restructuring of Medicare reimbursement from fee-for-service to bundled payment (Wikipedia). Effective October 1, 2012, CMS had begun Readmission Reduction Program, which penalizes IPP.S hospitals with excess readmissions.

The deregulation of prices in hospitals in the last two decades and emergence of managed care plans introduced selective contracting into the hospital market. Not all the hospitals get the contract and the decision largely depends on services, amenities, quality and price. In a recent article “The future of U.S. healthcare (The Wall Street Journal, Monday, December 12, 2011), the author has cited many examples where individual physician practices are shutting down. The hospitals are increasingly merging with other hospitals, and they are signing contract with employers. Insurance companies on the other hand are trying to acquire hospitals or signing new payment terms. In short the lines of distinction between hospitals and insurance companies are getting blurred.

There is a contract between a provider and insurer, whenever an individual gets services from a provider, insurer pays provider based on the contract terms. It has become overly important for both hospitals and insurance companies to look at their contractual terms for their better future. The above discussed models are not free from shortcomings. They all have advantages for one and risks for others, as summarized in Table 1.1. This research intends to use Industrial Engineering skills and the knowledge of Operations Research to develop an optimization model which will help providers design favorable contracts with insurers.

1.5 Expected Results

The model will help providers choose a reimbursement model or the combination of models from the mix of available reimbursement models that is best for their dynamic patient population and the facility, by:

a. helping providers in assessing reimbursement based on DRGs,

b. helping providers choose among different insurers, and

c. helping providers in deciding future investment (based of increase in number of patients from particular DRG or more profitable DRG, by increasing number of beds etc.) thus making them more competitive in market.

The rest of the manuscript is organized in several chapters. Chapter 2 deals with an extensive literature review with two parts. First part explains the available and proposed reimbursement models in healthcare. The section also enlists advantages and disadvantages of the models. Second part explains several techniques that have been used for negotiations in other industries in detail. The chapter also explain how DEA has been used in healthcare in general but has not been used for optimizing reimbursement plans in particular.

Chapter 3 is about methodology, classical Data Envelopment Analysis (DEA) and in combination with Principal Component Analysis (PCA DEA), used for designing optimization model. It explain in detail the formulation of optimization model.

In chapter 4 results obtained using DEA optimization model will be discussed. The chapter will explain advantages and disadvantages of the optimization model also discusses how DEA optimization model can help providers negotiate a contract with insurers that allows them to maximize their profit by reducing PACs.

Finally the manuscript will be concluded with suggestions for future research.

CHAPTER 2

LITERATURE REVIEW

Section 1

Inpatient reimbursement is calculated based a system called Acute Care Hospital Inpatient Prospective Payment System (IPPS). The way IPPS works is explained hereunder, the information gathered here is collected from Centers for Medicare & Medicaid Services' Department of Health and Human Services.

2.1 Background

A contract is written between a provider and Medicare to set acute IPP.S rates which a facility accepts. The contract covers the episode of care beneficiaries for 90 days of care per episode with an additional 60 days lifetime reserve. The episode of begins when a beneficiary is admitted and it ends when patient has been out of the facility for 60 consecutive days.

2.1.1 Basis of IPP.S Payment

The reimbursement received by the hospital for inpatients is either per case or per discharge based. "All the outpatient diagnostic services and admission related non-diagnostic services provided by the facility or an entity that is wholly owned or operated by the admitting facility on the date of patient's inpatient admission or within 3 days immediately preceding the admission must be included in the IPP.S claim".

For each patient hospital treats it files a claim to the Medicare Administrative Contractor (MAC). Based on the information on the claim MAC categorizes each case into Diagnostic

Related Group (DRG). DRG is a classification system was developed by Robert Barclay Fetter and John D. Thompson at Yale University with the material support of the former Health Care Financing Administration (HCFA), now called the Centers for Medicare & Medicaid Services (CMS) (Wikipedia). The DRG is determined with the help of a principal diagnosis and/or up to 24 comorbidities (secondary diagnosis). It is also affected by up to 25 procedures furnished by the facility during the stay of the patient. The CMS reviews the definitions of DRGs annually and make required changes.

Since October 1, 2007, CMS has started using new DRG system called Medicare Severity (MS)-DRG, which takes severity of illness and consumption of resources into consideration when assigning the DRG. Assigning the severity is based on secondary diagnosis which has 3 levels to it:

MCC – Major Complication/ Comorbidity, which reflect the highest level of severity,

CC - Complication/ Comorbidity, which is the next level of severity, and

Non-CC – Non-Complication/ Comorbidity, which do not significantly affect severity of illness and resources used.

2.1.2 Fee-For-Service Model (Massachusetts Medical Society, 2009)

Fee-For-Service (FFS) as the name suggests means insurer pays for services rendered by the provider based on CPG. The price of the services is established by negotiation between insurer and provider. Charges for all the services that a provider provides are generally listed on their fee schedule, which is based on set of 5 digit codes called Current Procedural Terminology (CPT).

In an ideal world it could be a good model for reimbursing providers, however for the most part it is the insurer who makes a decision of how much each service should be paid and hence provider feels underpaid. On the other hand there is equally high likelihood of over utilization of services and the model is more prone to be volume driven than value driven. Although this model has weaknesses, it is still the most common methods of reimbursing providers.

2.1.2.1 How do hospitals get paid under Medicare?

Medicare Part A Prospective payment system is method by which weight is given to DRGs submitted by hospital to CMS for claims submitted for the payment for the services provided to the patient. The Flow of information is shown in Figure 2.1 below. Similar method is followed by most of the private insurers which also works on DRGs.

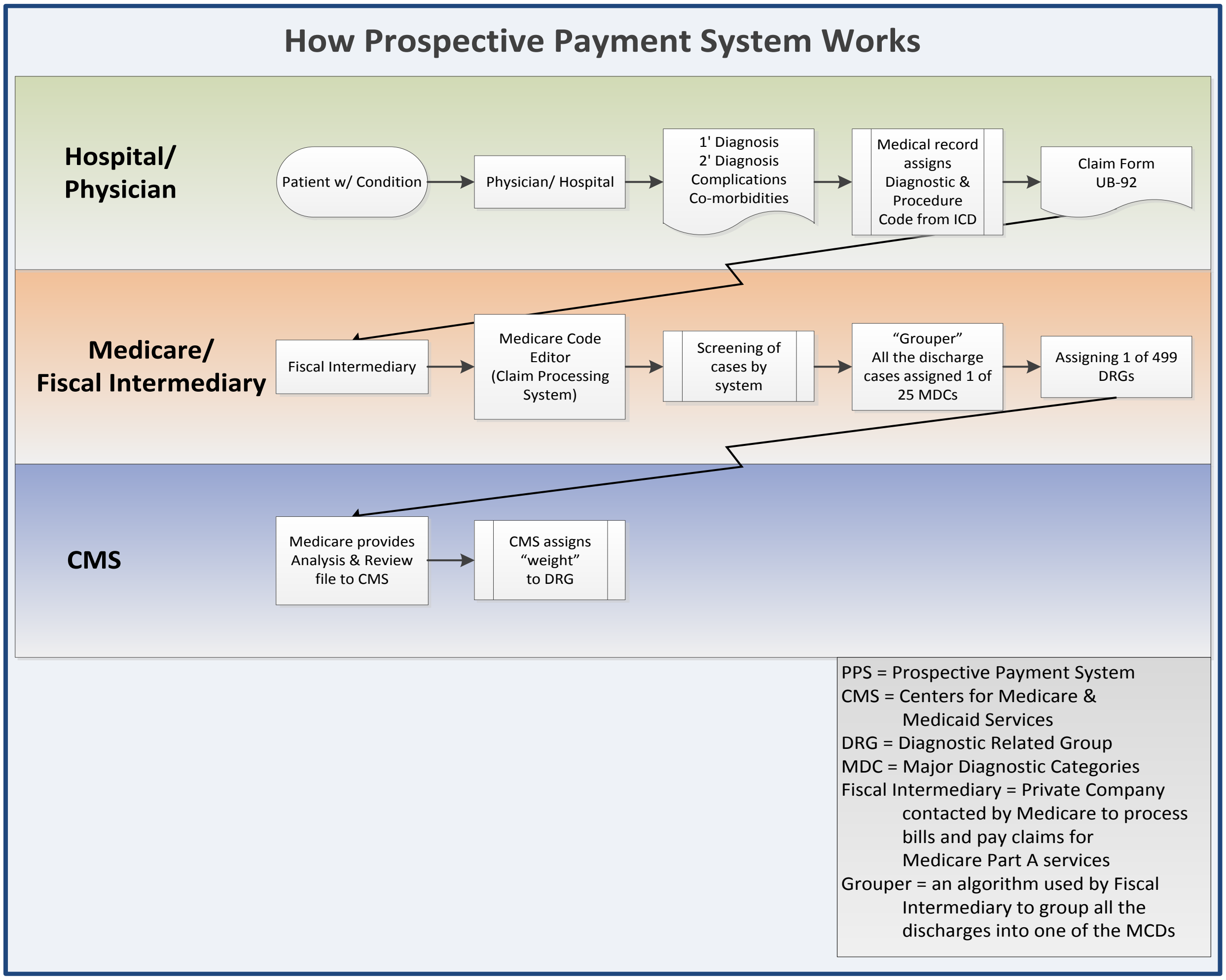


Figure 2.1: Flow of information from Hospital to CMS to claim DRGs

There is a complex formula to calculate the payment for hospital using DRGs by CMS, described in Figure 2.2 below. DRGs are classified according to the affected organ system, surgical procedure performed in patients, morbidity and sex of the patients. The system can account for 9 diagnoses per case, 1 primary and up to 8 diagnoses during the stay in the hospital. The system can also account for up to 6 procedures. DRGs cover both labor and no-labor costs (bundle services) and routine operating costs, such as, patient care, routine nursing services, room and boarding, diagnostics, ancillary services etc.

How Prospective Payment System Works

Calculating DRG weights
- patient charges are standardized to remove effects of the regional area wage differences
- indirect medical education costs
- additional payment to hospitals that treat a large percentage of low income patients ("disproportionate share payments")
- the cases outside 3 standard deviations are eliminated
- disproportionate share payments
- whether the hospital is a sole community hospital, Medicare dependent rural hospital (depends on Medicare for atleast 60% of its patient days or discharges), or a regional referral hospital

$$\text{Average standard charge} = \frac{\text{sum of charges of all cases in the DRG}}{\text{\# of cases classified in the DRG}}$$

$$\text{Weighting factor} = \frac{\text{Average charge of each DRG}}{\text{National average standardized charge per case}}$$

Hospital Payment = DRG weight x hospital's payment rate/case ("large urban" or "other")

Hospital Payment = DRG weight x standardized amount

where,

standardized amount = a "labor component" (representing labor cost variation among different parts of the country)

\+

a "non-labor component" (representing geographic calculation based on whether the hospital is located in a large urban or other area)

\+

if applicable:

cost outlier + disproportionate share + indirect medical education Payments

Note: DRG system does not include some specialized hospitals, such as, psychiatric, cancer, long-term care, children's, and rehabilitation hospitals

Figure 2.2: Calculating Dollar amount with respect to DRGs submitted to CMS

2.1.2.2 How do physicians get paid under Medicare?

Medicare Part B pays physicians based on CPT codes submitted by physicians' office to CMS for services provided to the patients. CMS in turn uses Resource-based Relative Value Scale (RBRVS) to assign relative weight to each code, which is later used in a formula to calculate dollar value for each CPT code submitted, as shown in Figure 2.3. This is a bottom-up methodology followed by CMS.

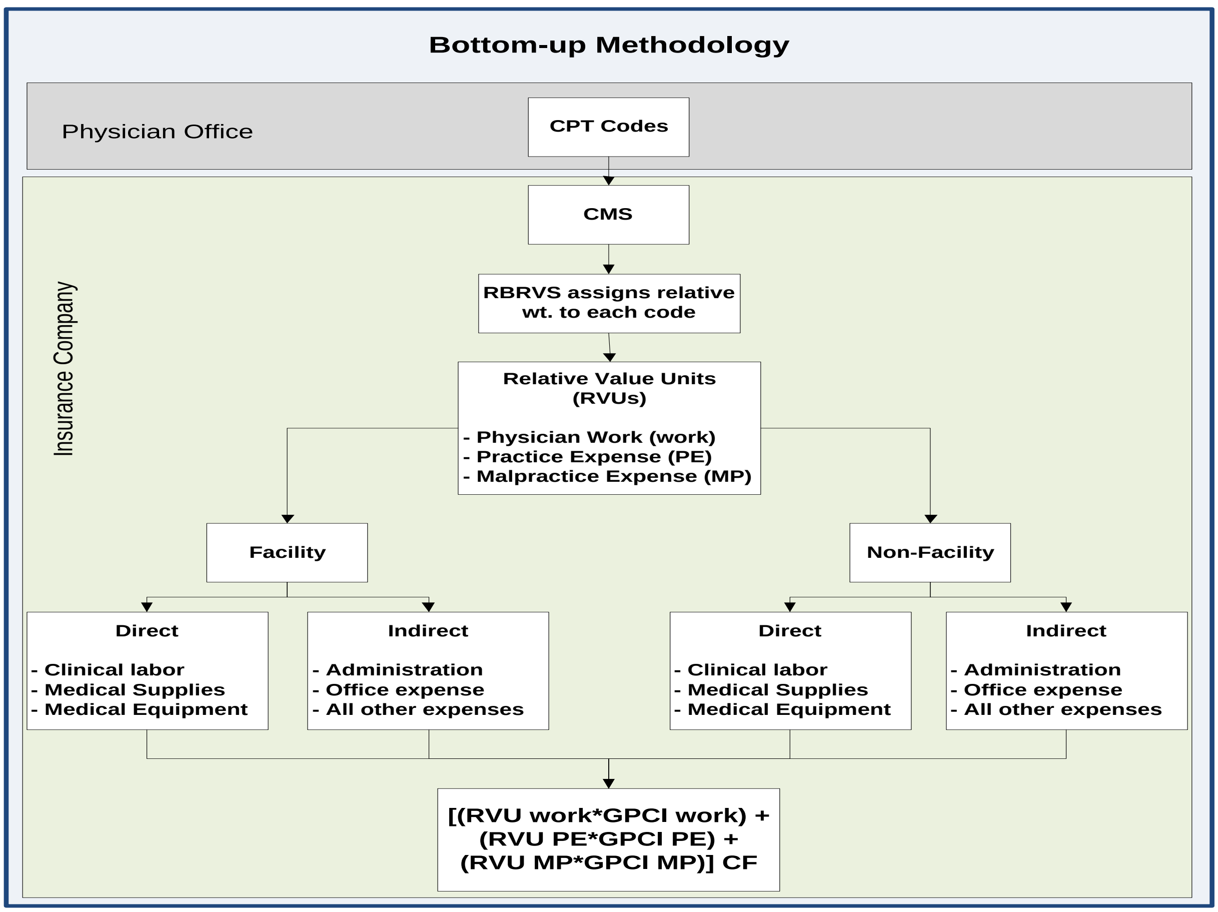


Figure 2.3: Calculating Dollar amount with respect to CPT codes submitted to CMS

2.1.3 Bundled Payments (Reese, 2010)

The Bundled Payments for Care Improvements Initiative was launched by CMS on August 23, 2011. The idea was to explore and study four distinct bundled payment models in an effort to achieve better health, better care, and reduced expenditures. Of the four models, as summarized in Table 2.1 below, three of them utilize a “retrospective” payment model in which Medicare makes a discounted traditional fee-for-service payment (in an agreement between CMS and the participant provider), which is subsequently reconciled against a target price. The fourth payment model uses a “prospective” payment approach, under which CMS makes a single bundled payment to the participating provider for an entire episode of care in lieu of traditional Part A and Part B fee-for-service payments. More importantly, CMS may permit gain sharing in all four models.

This is also called as “episode of care” or “case rate” payment. This means a single bundled payment made for a specific condition such as knee replacement or kidney transplant etc. The episode could include different specialists, different facilities, post-operative care etc. involved in an “episode”. The payment is typically made to the hospitals, which divide it among providers involved in the care. This kind of model is appropriate for acute cases such as heart attack, the conditions that have clear beginning and an end (Congressional Budget Office, 2008). In such a condition, under this model a single payment would be made to the provider.

Although this model has its drawbacks, but the model works well in certain cases, such as, acute conditions or different acute episodes of chronic conditions as explained in Figure 2.4.

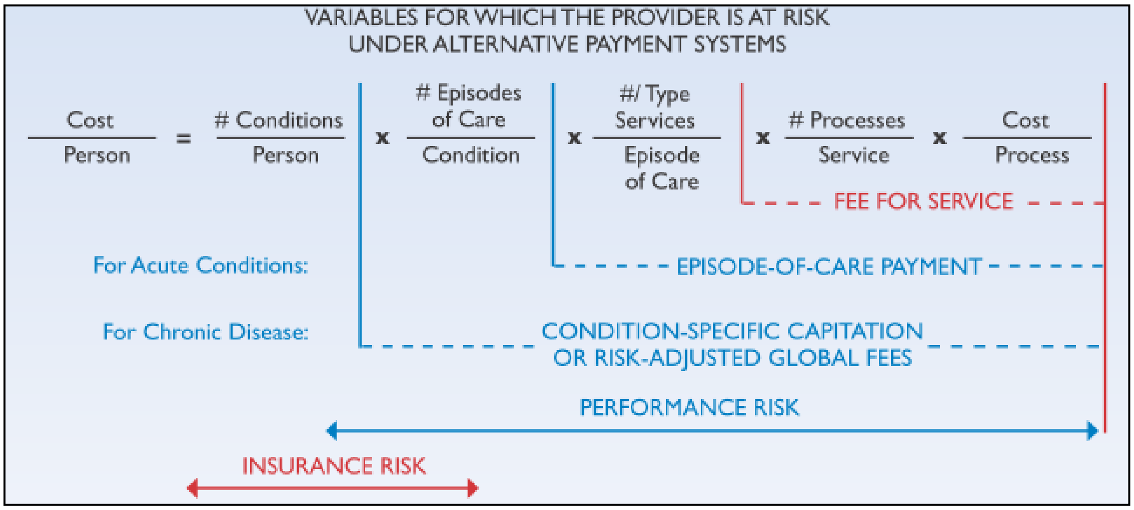


Figure 2.4: Variables for which the provider is at risk under alternative payment systems (Source: From Volume to Value, NRHI, 2009)

According to a report, *The Medicare bundled payments for care improvement initiative: An analysis and its implications to potential participants (2011)*, there are four different types of bundled payment models based on whether the patient is being treated for an acute or chronic condition. They are –

2.1.4.1 Model 1: Retrospective Acute Care Hospital Stay only

The episode of care in this model is focused on acute-care inpatient hospitalization. The episode of care begins with patient’s admission in a hospital and ends with his/her discharge from the hospital. It includes all Part A services furnished by the hospital (regardless of their particular MS-DRG) during patient’s stay including diagnostic and related services provided in 3 days prior to admission by the hospital and/or any entity wholly owned or operated by the hospital.

2.1.4.2 Model 2: Retrospective Acute Care Hospital Stay Plus Post-Acute Care

This model extends the episode of care to include both acute-care hospitalization as well as post-acute care following and associated with the acute-care episode. Unlike Model 1, Model 2 also includes physician and other Part B services associated with the episode for previously agreed upon MS-DRGs.

The episode begins with the admission of the patient and continues for a minimum of 30 days post-discharge. Hospital has 2 options to choose with respect to end of episode of care. In Option 1, the episode will end between 30 – 89 days post discharge and in Option 2, the episode will end a minimum of 90 days post discharge. The episode includes all Part A and Part B services provided during patient’s stay in the hospital as well as related services provided during post-discharge period including related readmissions.

2.1.4.3 Model 3: Retrospective Post-Acute Care Only

The episode of care is limited only to post-acute care following an acute inpatient hospital stay. The episode under the model begins with initiation of post-acute care services at a skilled nursing facility, inpatient rehabilitation facility, long-term care hospital, or home health agency within 30 days of patient’s discharge from an acute care hospital for an agreed upon MS-DRG.

2.1.4.4 Model 4: Prospective Acute Care Hospital Stay Only

"Model covers both Part A and Part B services furnished during episode of care. Like in Model 1, the episode of care involves only the "acute inpatient hospital stay" and it begins upon patient's hospital admission. However, unlike Model 1, there is no clarity on when the episode of care ends in Model 4. First, the indication is that the episode ends upon discharge for the acute care hospital and includes all Part A and Part B services provided during patient's stay, including services rendered during Medicare 3-day window payment bundling rule. Episode of care in Model 4 also includes Part A and Part B services provided during "related admissions", but "post-discharge" period is to be defined by the hospital for the agreed upon MS-DRGs in the beginning of contract. In contrast to Model 1, Model 4 includes one single prospective bundled payment for both Part A and Part B services'.

As mentioned earlier there are 4 types of bundled payment models. Table 2.1, shows the methodology for calculating amount to be paid under all the 4 models.

Table 2.1: Calculating Dollar amount with respect to Bundle Model of Payment

FEATURE	MODEL 1 – Inpatient Stay Only	MODEL 2 – Inpatient Stay + Post-discharge Services	MODEL 3 – Post-discharge Services Only	MODEL 4 – Inpatient Stay Only
Eligible Awardees	• Physician group practices • Acute care hospitals paid under the IPP.S • Health systems • Physician-hospital organizations • Conveners of participating healthcare providers	• Physician group practices • Acute care hospitals paid under the IPP.S • Health systems • Physician-hospital organizations • Conveners of participating healthcare providers • Post-acute providers	• Physician group practices • Acute care hospitals paid under the IPP.S • Health systems • Physician-hospital organizations • Conveners of participating healthcare providers • Long-term care hospitals • Inpatient rehabilitation facilities • Skilled nursing facilities	• Physician group practices • Acute care hospitals paid under the IPP.S • Health systems • Physician-hospital organizations • Conveners of participating healthcare providers
Payment of Bundle and Target Price	Discounted IPP.S payment No separate target price	Retrospective comparison of target price and actual FFS payments	Retrospective comparison of target price and actual FFS payments	Prospectively set payment
Clinical Conditions Targeted	ALL MS-DRGs	Applicants to propose based on MS-DRG or inpatient hospital stay	Applicants to propose based on MS-DRG or inpatient hospital stay	Applicants to propose based on MS-DRG or inpatient hospital stay
Types of Services Included in Bundle	Inpatient hospital services	• Inpatient hospital and physician services • Related post-acute care services • Related readmissions • Other services defined in the bundle	• Post-acute care services • Related readmissions • Other services defined in the bundle	• Inpatient hospital and physician services • Related readmissions
Expected Discount Provided to Medicare	To be proposed by the applicant CMS requires minimum discounts increasing from 0 % in first 6 months to 2 % in year 3	To be proposed by the applicant CMS requires minimum discount of 3 % for 30 – 89 days post discharge episode, 2 % for 90 days or longer episode	To be proposed by applicant	To be proposed by applicant Subject to minimum discount of 3% Larger discount for MS-DRGs in ACE Demonstration
Payment from CMS to providers	• Acute care hospital: IPP.S payment less pre-determined discount • Physician: Traditional fee schedule payment (not included in episode)	Traditional fee-for-service payment to all providers and suppliers, subject to reconciliation with predetermined target price	Traditional fee-for-service payment to all providers and suppliers, subject to reconciliation with predetermined target price	Prospectively established bundled payment to admitting hospital; hospitals distribute payments from bundled payment

2.1.5 PROMETHEUS Payment (Terry, 2010)

PROMETHEUS which stands for Provider Payment Reform for Outcomes Margins Evidence Transparency Hassle-reduction Excellence Understandability and Sustainability was result of a joint effort of a team composed of stakeholders (Massachusetts Medical Society, 2008). This model is a modification of fee-for-service payment model. The physicians are paid for fee for service, but also receive high bonuses for providing uncomplicated and efficient care to the patients.

The model is arguably the most advanced payment reimbursement model currently available. The model is based on guidelines established by Clinical Practice Guidelines (CPGs). CPGs include guidelines for all the steps, resources etc. required to treat a specific condition. The difference between “episode of care” or bundled payment model is that it risk is shared by both insurers and physicians (Massachusetts Medical Society, 2008).

PROMETHEUS Payment intends to fix the shortcomings rather than replacing the two most prevalent payment models in the US, namely Fee-for-service and capitation. The models attempts to create a payment structure where providers and insurers get incentivized when they do the right thing for the patients.

There are three important improvements over the previous models which differentiate it from them.

- Evidence-based guidelines are setup as a basis for establishing case rate, which also includes patient severity of disease. Outstanding performance can get more than 100% of the case rate.

- Model encourages integration of services around the patient measured on the basis of clinical process, outcomes of care, patient experience with care received and sometimes cost efficiency.

- The structure of the model encompasses a wide range of specialties from large integrated delivery networks to individual practitioners.

In Figure 2.5, PROMETHEUS model pays providers based on the most of the resources required to deliver CPG based care, which is an ECR. The model uses ECR to determine the total resources required to deliver clinical appropriate care. ECR calculates payment for the whole time patient stays in the hospital. After the payment amount has been negotiated for a provider treating within an ECR, provider has two methods of payment – prospective, and fee-for-service with retrospective reconciliation. It is up to provider to choose the payment mechanism.

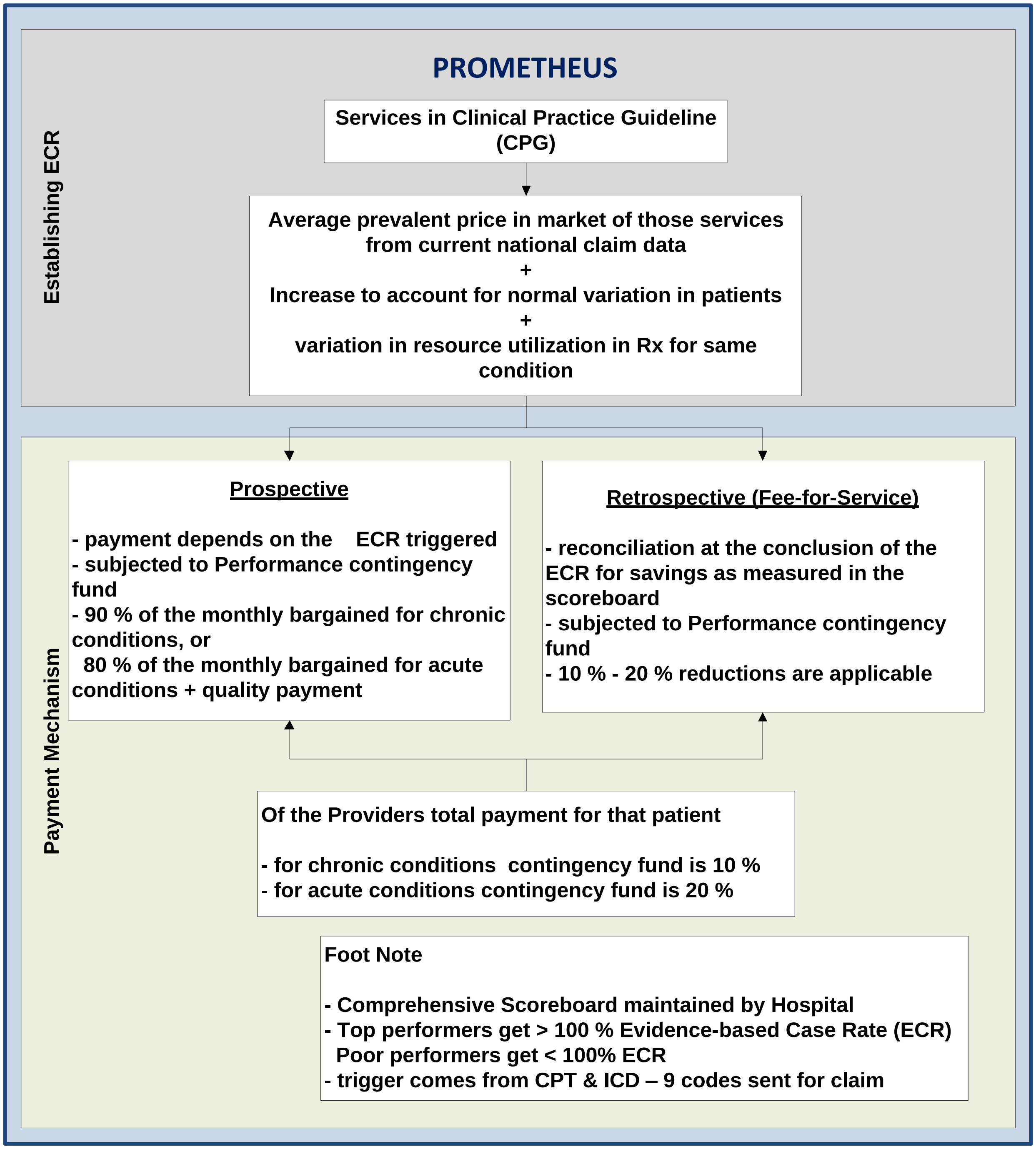


Figure 2.5: PROMETHEUS Model of Payment

Section 2

Reimbursement rates negotiated by hospitals and insurers are regarded as trade secrets which are rarely made available to public. For this apparent reason there has been little research analyzing variation in rates among insurers. Melnick *et. al.*, (1992) focused on the influence of hospital competition on discounts offered by analyzing the data on negotiated per diem rates across hospitals for California's largest PP.O. They used Hirschman-Herfindahl indexes to measure hospital competition. MEDSTAT database consisting of claims from employees of self-insured firms was analyzed for payment rates for appendectomies performed in the hospital. Using limited data covering few insurers for large number of hospitals, the authors were able to conclude factors determining bargaining power of providers e.g. hospital concentration, ownership type, affiliations etc. (Brooks *et. al.*,, 1997).

In contrast to the studies mentioned, Staten *et. al.*, (1998) focused on determinants of insurer bargaining power. The authors argue that size of insurer alone is not enough to get discounts from the hospital. "Insurer must be able to credibly threaten to send its patients elsewhere." Sometimes the patient may be more loyal to a hospital than to an insurer and in that case even managed care organizations may not be able to enforce such a threat. Alan T. Sorensen (2001) analyzed the data from state of Connecticut and not to his surprise Health Maintenance Organizations (HMOs) and Preferred Provider Organizations (PPOs) were able to get bigger discounts which increase with the size of insurer. He also concluded size alone is not the determinant of discount and it requires insurers' ability to channel the patients to selected providers. He also found "charges incurred by Managed Care Organizations (MCOs) tend to be highly skewed toward hospitals with which discounts have been negotiated, and more highly skewed allocations tend to be associated with larger discounts." Contrary to the conventional wisdom in the healthcare industry that "volume is the king", the econometric model suggested that "patient channeling" is more important in determining discounts than the insurer size.

A model is a representation of relationship between different variables, they are generally theoretical. In economics, underlying structural parameters are used to construct a simplified framework of complex processes. Mathematical techniques are often used to show the interaction between a set of variables (Wikipedia). Operations research which is also referred to as decision science employs various techniques and tools to arrive at optimal or near optimal solutions. Some of the tools or methods used in operations research are optimization, probability theory, queuing theory, game theory, graph theory, decision analysis, mathematical modeling and simulation. The use of technique depends on various factors, such as, nature of the system, the goals of improvement, and constraints on time (bls.gov).

The chosen problem in healthcare can be compared to a scenario in which there are multiple firms (hospitals) selling same product (services) trying to attract customers (patients) from a common pool. There are several constraints involved, like capacity (number of beds, physicians, nurses, etc.), specialty if any (pediatric hospital, cancer hospital, etc.), insurance company coverage and their contracts etc. Processes in healthcare are more often stochastic in nature and hence there is always a possibility of choosing one path over the other. A model could be either quantitative or qualitative according to its intended purpose or function. There are many models that have been developed to solve such a problem in different industries.

Pauly and Redisch (1973), their work still serves as the basis of modeling the hospital-physician interaction in economics. In their model they considered hospitals as cooperative organization largely run by physicians having control of hospital resources. Their model was clearly meant to work to maximize physicians' income and hence had lot of drawbacks.

According to Brooks *et. al.*, (1997) there is a potential gain from negotiations by both insurers and provider. They used Nash-bargaining model to estimate hospital-insurer negotiation over prices. They concluded that hospitals have relatively more bargaining power than insurers because of the greater enrollment of population in HMOs that has positive impact on the hospital bargaining power with respect to Fee-for-service plans. However there were some methodological issues with the study, like the model considered the relationship to be bilateral monopoly instead of bilateral oligopoly, and there are no generalizations of Nash-bargaining model for the former. This concern reduces the applicability of the model to the real world healthcare market.

Morrisey (2001) concluded selective nature of contracts between healthcare insurers and providers has provided formers to obtain lower prices from HMOs. He also concludes that the findings are not only generalizable but also stringer when there is more competition in hospital market. This potentially means insurers can threaten hospitals by removing them from their network.

Several techniques have been utilized previously to study the process of negotiation between market players and most of them have applied in manufacturing and service industries. Wang and Zionts (2008) considered a problem which had one buyer and many sellers, called "one-to-many negotiation problem". They used BATNA (Best Alternatives To a Negotiated Agreement) to measure the strength of negotiation and also developed guidelines to help in the bargaining process. Using this technique, they were not only able to measure strength of negotiation but also settle on one criterion from several available alternatives.

Stanley Zionts (1979) authored an article "MCDM-If not a Roman Numeral, then What?" MCDM or MCDA stands for Multiple Criteria Decision Making or Multiple Criteria Decision Analysis. It is a field of operations research that deals with multiple criterions while making decisions. One of the major uses of the technique is negotiating cost or price. Since the problem involving multiple criterions do have a specific solution, it provides several options to decision maker to choose from.

According to Wallenius *et. al.*, (2008), the potential of MCDM is being explored in new areas of research and application such as, Data Envelopment Analysis (DEA), negotiation science, e-commerce, finance, and engineering. They went on further to say that DEA has gained so much importance that its relationship with Multiple Objective Linear Programming (MOLP) is also being explored.

One of the pioneering works in the field of goal programming and DEA was conducted by Charnes and Cooper (Charnes and Cooper, 1961; Charnes *et. al.*, 1978). The basic difference between MOLP and DEA lies in the fact that former uses more general nonradial projections compared to radial projections used in the later technique. In other words, MOLP is more generic and can be used in benchmarking studies. Whereas DEA is more specific and is used for performance measurement of available alternatives (Joro *et. al.*, 1998).

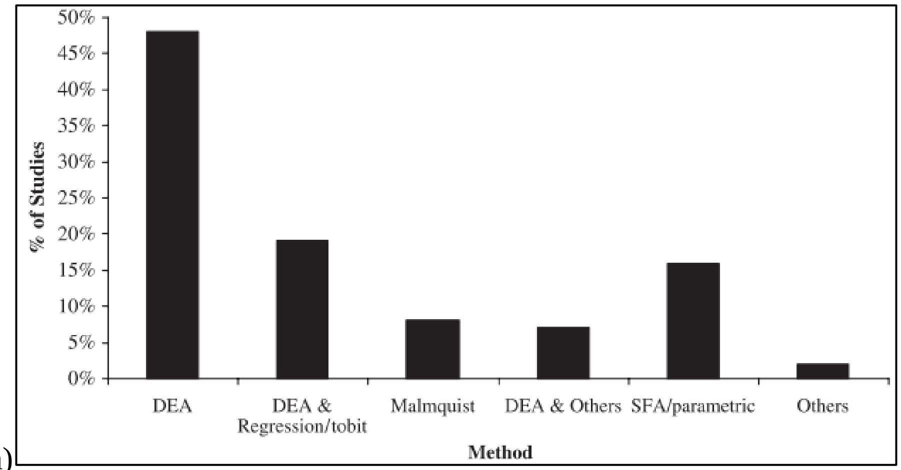
2.6 Data envelopment analysis

Data Envelopment Analysis is a non-parametric productive efficiency measurement method for operations with multiple inputs and multiple outputs (Liu *et. al.*, 2013). According to Seiford (1996), DEA in its current form was first described in Charnes *et. al.*, (1978), who proposed a novel method that combines and transforms multiple inputs and outputs into a single efficiency index. This approach first establishes an "efficient frontier" formed by a set of decision making units (DMUs) that exhibit best practices and then assigns the efficiency level to other non-frontier units according to their distances to the efficient frontier. The basic idea has since generated a wide range of variations in measuring efficiency. Today, various DEA efficiency models, such as the constant returns to scale (CRS) model, the variable-returns-to-scale (VRS) model, the additive model, the slacks-based measures and the free disposal hull (FDH) model, etc. are available for different types of measuring requirement. It also has been applied to various industrial and non-industrial contexts, such as banking, education, hospital, etc. (Emrouznejad *et. al.*, 2008).

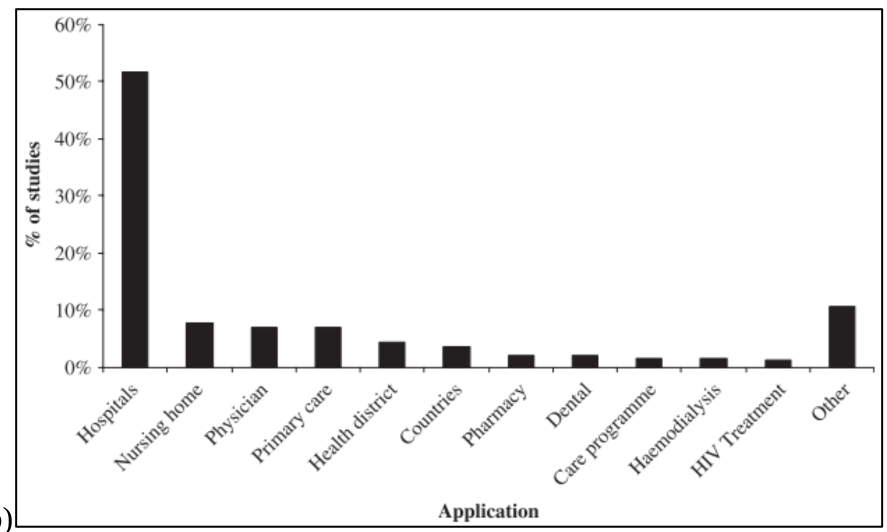
Pioneers of data envelopment analysis (DEA) may not have expected that their ideas have inspired the thinking of a group of researchers and have been developed collectively into a widely accepted academic field. Thirty some years after the publication of the seminal paper by Charnes *et. al.*, (1978), the development continues and has not seen any signs of weakening. In 2009 alone, more than 700 DEA papers were published. Up through the year 2009, the field has accumulated approximately 4500 papers in ISI Web of Science database.

2.6.1 DEA applied to healthcare systems

Since the early 1980s, Hollingsworth (2008) reviewed papers that had used efficiency analysis to measure and analyze the productive performance of healthcare services. As shown in Figure 2.6, DEA has been used in over 75 per cent of frontier efficiency analysis, and furthermore over 50 per cent of applications are in hospitals. Most studies use output (or throughput) measures of physical performance, such as inpatient days or discharges. There is some use, in 9 per cent of studies, of outcome measures examining changes in health status, mortality or quality of care for individuals treated. Input variables are mainly measures of staff and capital employed, and most analysis is of technical efficiency.



(a)



(b)

Figure 2.6: (a) Methods and (b) areas of app.lication in efficiency analysis of healthcare services. Hollingsworth (2008).

2.6.2 DEA and negotiation science

The literature on negotiation and group decision making is broad and diverse. The field is multidisciplinary, involving different approaches by social psychologists, economists, and management scientists. Reviewing published papers regard to multiple criteria decision making (MCDM) and multiattribute utility theory (MAUT), Wallenius *et. al.*, (2008) stated that MCDM/MAUT has begun to penetrate many new areas of research and applications such as decision analysis, mathematical programming, DEA, and negotiation analysis. Yet, MCDM and DEA developed separately; Belton (1992) and Doyle and Green (1993) described the relationships between the two. Subsequently, Joro *et. al.*, (1998) developed a detailed understanding of the structural (mathematical) relationship between DEA and MOLP, and noted the close similarities that exist.

Negotiation is a way for parties to reach agreement in a dispute or in making a joint decision. In general, negotiations involve one or more issues that need to be settled between two or more involved parties (Raiffa, 1982). DEA app.roach, according to Cook and Seiford (2009), is a non-parametric technique which allows us to measure, by solving a linear programming system, the performance of a subject and to assign to it a score representing its efficiency performance. In a recent publication, Wang and Zionts (2008) tied together various existing material on negotiation, and propose a quantitative framework, based on existing research concepts, for carrying out negotiations. The authors used analysis similar to DEA to come up with a measure of efficiency and to choose the best alternative with various input and output measures.

CHAPTER 3

METHODOLOGY

Data Envelopment Analysis (DEA) is used to determine relative efficiencies between decision making units (DMU) which was first developed by Charnes *et. al.,* (1978). A DMU can be any entity, but in this manuscript it refers to the different reimbursement models. DEA helps to distinguish between efficient and inefficient DMUs (reimbursement models). Linear Programming is the platform for which DEA analyzes the different reimbursement models. It uses a non-parametric method which does not need a production function to determine efficiency which is the DMU output/ DMU input ratio. The goal is to enhance efficiency by decreasing inputs or increasing outputs. This implies in this manuscript to reducing PACs to enhance hospital profitability.

DEA can be compared to statistical regression analysis as it has similar objectives. Regression provides the "average" performance of a DMU, but DEA compares all the DMUs to the most efficient DMU being analyzed. The advantage of DEA is that the most efficient DMU becomes the "benchmark". This DMU becomes a target for other less efficient DMUs in the reference set. Regression analysis does not distinguish the efficient DMU from the inefficient DMUs.

3.1 DEA formulation

The DEA model considers a set of n DMUs where each DMU j, ($j=1,...,n$) uses m inputs x_{ij} ($i=1,...,m$) to generate s outputs y_{rj} ($r=1,...,s$). Given that all inputs and outputs are not equally weighted, multipliers are introduced to distinguish among inputs and outputs. If the multipliers $\bar{u}_r$, $\bar{v}_i$ associated with outputs r and inputs i, respectively, are known, then conventional benefit/cost theory can express DMU technical efficiency $\bar{e}_j$ as the ratio of weighted outputs to weighted inputs.

$$\sum_r \bar{u}_r y_{rj} \Big/ \sum_i \bar{v}_i x_{ij} \tag{3.1}$$

According to Cook and Seiford (2009), the benefit/cost ratio above is the basis for the standard engineering ratio of productivity. In the absence of known multipliers, Charnes *et. al.*, (1978) proposed deriving appropriate multipliers for a given DMU by solving a particular non-linear programming problem. Charnes *et. al.,* (1978) model for measuring the DMU technical efficiency is provided for the following fractional programming problem:

$$\begin{aligned} e_o = \max \quad & \sum_r u_r y_{ro} \Big/ \sum_i v_i x_{io} \\ s.t. \quad & \sum_r u_r y_{rj} - \sum_i v_i x_{ij} \le 0, \quad \forall j \\ & u_r, v_i \ge \varepsilon > 0, \quad \forall r, i. \end{aligned} \tag{3.2}$$

where, ε is a non-Archimedean value designed to enforce strict positivity on the variables. Equation 3.2 is referred to as the Charnes, Cooper and Rhodes (CCR) model. It provides for Constant Returns to Scale (CRS). This original publication on DEA simply restricted the variables to be non-negative (ε=0). The imposition of a strictly positive lower limit (ε>0) was introduced in a follow-up paper, Charnes *et. al.*, (1981).

It is essential to point out that the CCR model in Equation (3.2) is referred to as the *input-oriented* minimization model. The inversion of the CCR model illustrated in Equation (3.2) is referred to as the *output-oriented* minimization problem. This fractional programming problem is converted to linear programming problem by applying the Charnes and Cooper (1962) theory. This specifically refers to changing $\mu_r = tu_r$ and $\upsilon_i = tv_i$, such that $t = \left(\sum_i v_i x_{io}\right)^{-1}$. The linear programming formulation is presented in Equation. (3.3).

$$
\begin{aligned}
e_o = \max \quad & \sum_r \mu_r y_{ro} \\
s.t. \quad & \sum_i \upsilon_i x_{io} = 1 \\
& \sum_r \mu_r y_{rj} - \sum_i \upsilon_i x_{ij} \leq 0, \quad \forall j \\
& \mu_r, \upsilon_i \geq \varepsilon, \quad \forall r, i.
\end{aligned}
\tag{3.3}
$$

The equivalent minimization linear programming formulation is presented in equation (3.4).

$$
\begin{aligned}
\min \quad & \theta_o - \varepsilon\left(\sum_r s_r^+ + \sum_i s_i^-\right) \\
\text{s.t.} \quad & \sum_j \lambda_j x_{ij} + s_i^- = \theta_o x_{io}, \quad i = 1, \ldots, m \\
& \sum_j \lambda_j y_{rj} - s_r^+ = y_{ro}, \quad r = 1, \ldots, s \\
& \lambda_j, s_i^-, s_r^+ \geqslant 0, \quad \forall i, j, r \\
& \theta_o \text{ unconstrained.}
\end{aligned}
\tag{3.4}
$$

Equation (3.4) is referred to as the envelopment or primal problem, and Equation (3.3) is the multiplier or dual problem. To get a geometric appreciation for the CRS model, one can represent problem (3.3) in a graphical form such as Figure 3.1.

DMU	1	2	3	4	5	6	7
X	2	3	6	9	5	4	10
Y	2	5	7	8	3	1	7

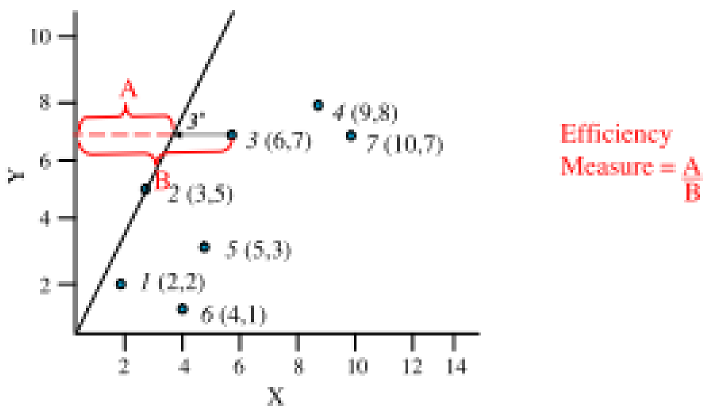


Figure 3.1: single input single output example. (Source: Cook and Seiford, 2009)

Figure 3.1 provides an illustration of a single input single output case. Solving Equation (3.3) for each of the DMUs illustrates that DMU #2 is the most efficient. The efficient frontier is plotted by connecting a line from the origin through DMU #2. Any DMUs to the right of this efficient frontier line represents the inefficient DMUs. For example DMU #3 is an inefficient DMU. Its projection to the efficient frontier is represented by the point 3*. The relative efficiency of DMU #3 is measured as the ratio A/B = 4.2/6 = .70. DMU #3 is 70% as efficient as DMU #2.

An alternative geometric view of Equation (3.3) is provided in Figure 3.2.

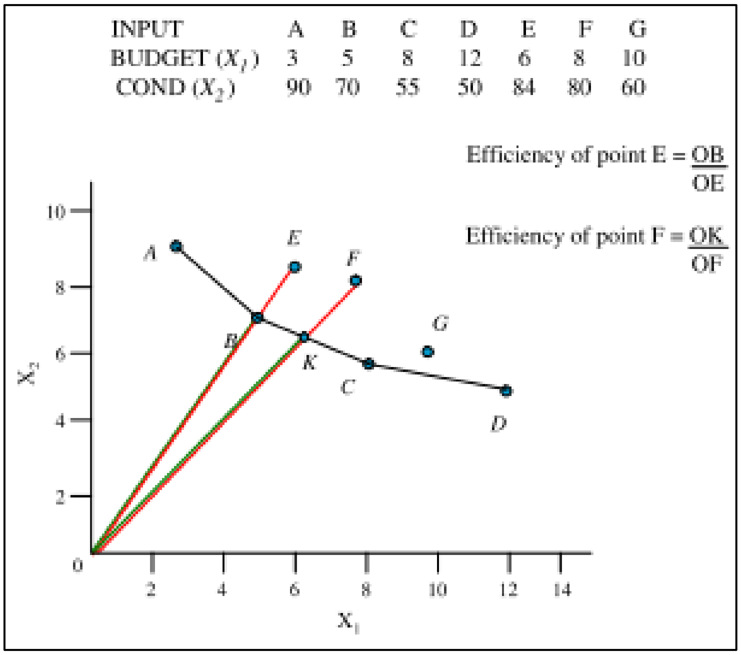


Figure 3.2: A two input one output example. (Source: Cook and Seiford, 2009)

Solving Equation (3.3) results in DMUs A, B, C and D being identified as efficient (, i.e., $\theta_A = \theta_B = \theta_C = \theta_D = 100\%$). The CCR model is appropriately utilized to provide the radial projection. Specifically, each input is reduced by the same proportionality factor θ. DMU E θ_E = 83.3% efficient, and the resulting projected value $\theta_E^* x_E$ is simply the frontier DMU B. DMU B is the ‘‘benchmark” for DMU E. DMU G projection to the efficient frontier is point K. Therefore DMU B and DMU C are appropriate benchmarks for DMU G.

DEA has been universally recognized as a useful tool of performance assessment, but very often more than one DMU is evaluated as DEA efficient, which makes DEA efficient units unable to be compared or ranked. Therefore, the assurance region concept was developed, initially by Thompson *et. al.* (1986, 1990) to prohibit large differences in the values of multipliers, and imposes constraints on the relative magnitudes of those multipliers. In this manuscript the non-Archimedean condition is $\varepsilon = \left(\sum_{i=1}^{m} x_{io}\right)^{-1}$. This discrimination impact of assurance region restrictions can be visualized in Figure 3.3. DMUs that are efficient in an unrestricted setting ($\varepsilon = 0$), such as DMU D in Figure 3.2, may be rendered inefficient as in Figure 3.3. Details on imposing minimum weight restrictions on inputs and outputs to provide discrimination between DMUs can be found in Wang *et. al.* (2009).

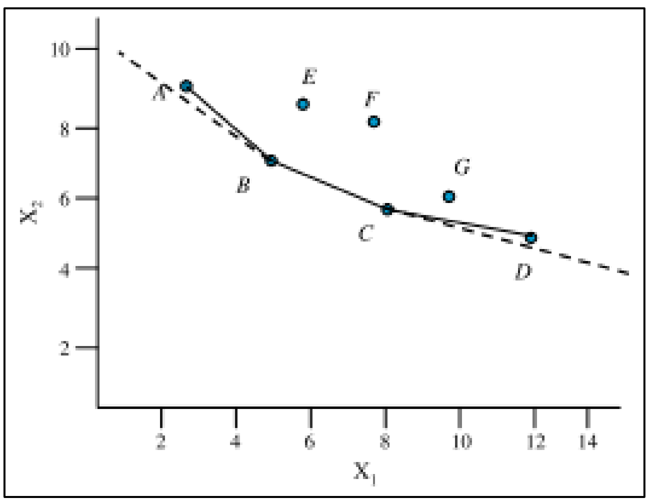


Figure 3.3: Impact of assurance region restrictions. (Source: Cook and Seiford, 2009)

3.2 PCA formulation

3.2.1 Overview

Principal Component Analysis (PCA) is a multivariate statistical technique first introduced by Hotelling (1933) to explain variance-covariance structure in a data set, using linear combinations of the original variables. According to Johnson and Wichern (2007) and Rencher (2002), its main objectives are: (1) reduction of dimensionality, and (2) data interpretation.

Although q components are necessary to reproduce the overall variability of a system, most of this variability can be represented by a small number k of principal components. This means that there is almost as much information on k principal components as in the q original variables. Therefore, the general idea of PCA is that k principal components can be substituted, without significant loss of information, by q original variables. The original data set consisting of n positions (of observations) of the q variables is reduced to a set of n positions (scores) of k principal components.

According to Rencher (2002), PCA often reveals relationships that were not previously identified with the original set, which results in a broader interpretation of the phenomenon under study. Johnson and Wichern (2007) validate PCA as an intermediate step in the data analysis.

Gabrielsson *et. al.* (2003b) define PCA as a least squares fit of a straight line or a plane/hyperplane that is N-dimensional (for data) in a K-dimensional space of principal components. In the case presented by Figure 3.4 which is adapted from Gabrielsson *et. al.* (2003b), the data are centered on the average and three original variables are described by only two principal components. The object is projected onto the mathematical plane described by the components, and the scores on each component are obtained by determining the distances between the origin and the projected object. Eigenvectors, also called "loadings", represent the coefficients of direction of the fitted plan. The perpendicular distance between the object and the plane is the distance to the model.

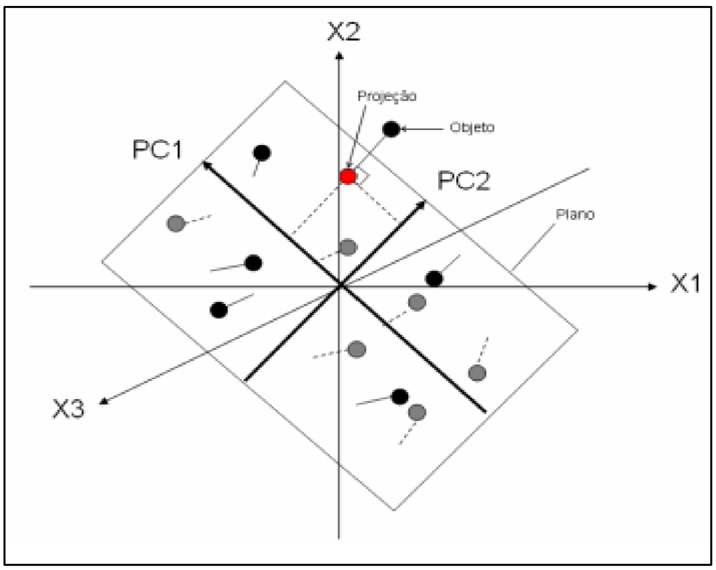


Figure 3.4: Geometric interpretation of PCA. (Source: Gabrielsson et. al., 2003)

3.2.2 Algebraic approach

Principal component analysis is one of the most widely used tools applied to summarize common patterns of variation among variables. Algebraically, it is a linear combination ℓ of q random variables Y_1, Y_2, …, Y_q. Geometrically, these combinations represent a new coordinate system obtained during the rotation of the original system (Johnson and Wichern, 2007; Mukherjee and Ray, 2008; Paiva *et. al.*,2008; Peruchi *et. al.*, 2013). The axes are now the variables Y_1, Y_2, …, Y_q and represent the direction of maximum variance. Principal components are uncorrelated and depend only on the covariance matrix $\mathbf{\Sigma}$ (or the correlation matrix $\boldsymbol{\rho}$) of the variables Y_1, Y_2, …, Y_q and its development does not require the assumption of multivariate normality .

The required information to obtain the scores of the first principal component (PC_1), as defined by Johnson and Wichern (2002), come from the linear combination that is able to maximize the variance, in accordance with Equation (3.5).

$$\begin{aligned} &Maximize: && Var\left(\mathbf{e}_1'\mathbf{Y}\right) \\ &Subject\ to: && \mathbf{e}_1'\mathbf{e}_1 = 1 \end{aligned} \tag{3.5}$$

In the optimization problem above, the product of the decision variables are limited to unit length, for eliminating indeterminacy of the solution, since $\mathbf{e}_1$ can be multiplied by any scalar. To obtain the scores of the second principal component (PC_2), the problem represented in Equation (3.5) is changed into Equation (3.6) to guarantee PC_1 and PC_2 being orthogonal vectors.

$$\begin{aligned} &Maximize: && Var\left(\mathbf{e}_2'\mathbf{Y}\right) \\ &Subject\ to: && \mathbf{e}_2'\mathbf{e}_2 = 1 \\ & && Cov\left(\mathbf{e}_1'\mathbf{Y}, \mathbf{e}_2'\mathbf{Y}\right) = 0 \end{aligned} \tag{3.6}$$

In general, the i^{th} principal component is the solution for the linear combination $\mathbf{e}_i'\mathbf{CTQ}$ which maximizes the variance in Equation (3.7):

$$\begin{aligned} &Maximize: && Var\left(\mathbf{e}_i'\mathbf{Y}\right) \\ &Subject\ to: && \mathbf{e}_i'\mathbf{e}_i = 1 \\ & && Cov\left(\mathbf{e}_i'\mathbf{Y}, \mathbf{e}_k'\mathbf{Y}\right) = 0 \quad para \quad k < i \end{aligned} \tag{3.7}$$

The result of the lexicographical optimization problem described above determines the eigenvalues as solution to the objective function and the optimal solution of the decision variables which are represented by the eigenvectors of each principal component. Using the pairs of eigenvalues and eigenvectors of each principal component (λ_1, $\mathbf{e}_1$), (λ_2, $\mathbf{e}_2$), ..., (λ_q, $\mathbf{e}_q$) where $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_q \geq 0$, the principal component scores can be calculated by linear combination below

$$\mathbf{PC}_i = \mathbf{e}_i'\mathbf{Y} = \mathbf{e}_{1i}\mathbf{Y}_1 + \mathbf{e}_{2i}\mathbf{Y}_2 + \ldots + \mathbf{e}_{qi}\mathbf{Y}_q \quad i = 1,2,\ldots,q \tag{3.8}$$

as well as the percentage of explanation of the i^{th} principal component using

$$\frac{\lambda_i}{\sum_{j=1}^{q}\lambda_j} \quad i = 1,2,\ldots,q \tag{3.9}$$

The principal components may also be obtained by the standardized variables

$$\begin{aligned} Z_1 &= \frac{(X_1 - \mu_1)}{\sqrt{\sigma_{11}}} \\ Z_2 &= \frac{(X_2 - \mu_2)}{\sqrt{\sigma_{22}}} \\ \vdots \quad & \quad \vdots \\ Z_q &= \frac{(X_q - \mu_q)}{\sqrt{\sigma_{qq}}} \end{aligned} \tag{3.10}$$

In matrix notation,

$$\mathbf{Z} = (\mathbf{V}^{1/2})^{-1}(\mathbf{X} - \boldsymbol{\mu}) \tag{3.11}$$

where $\mathbf{V}^{1/2}$ is the diagonal matrix of standard deviation. Clearly, E ($\mathbf{Z}$) = 0, and

$Cov(\mathbf{Z}) = (\mathbf{V}^{1/2})^{-1}\boldsymbol{\Sigma}(\mathbf{V}^{1/2})^{-1} = \boldsymbol{\rho}$. The principal components scores of Z can be obtained from the eigenvectors of the correlation matrix $\boldsymbol{\rho}$ of $\mathbf{Y}$. All previous results apply, with some simplifications, since the variance of each Z_i is unity. The notation will be the same for PC_i

referring to the i^{th} principal component and (λ_i, $\mathbf{e}_i$) for pairs of eigenvalue-eigenvector of the matrix $\mathbf{\Sigma}$ or $\boldsymbol{\rho}$. However, (λ_i, $\mathbf{e}_i$) derived from $\mathbf{\Sigma}$ is generally not exactly the same as derived from $\boldsymbol{\rho}$.

Johnson and Wichern (2007) determine that the assumption of multivariate normality is not required. Moreover, $\hat{\mathbf{\Sigma}}$ has pairs of eigenvalues-eigenvectors $(\hat{\lambda}_i, \hat{\mathbf{e}}_i)$ that are the same for the matrix sample variance-covariance $\mathbf{S}$. Therefore, both $\mathbf{S}$ and $\hat{\mathbf{\Sigma}}$ provide the same sample principal components $\mathbf{e}_i'\mathbf{Y}$ and the same percentage of explained variance $\lambda_i \Big/ \sum_{j=1}^{q} \lambda_j \quad i = 1,2,\ldots,q$.

Finally, both $\mathbf{S}$ and $\hat{\mathbf{\Sigma}}$ provide the same correlation matrix $\mathbf{R}$, then if the variables are standardized, the choice of $\mathbf{S}$ or $\hat{\mathbf{\Sigma}}$ is irrelevant.

3.2.3 Deciding how many principal components to analyze

In any application, a decision should be taken in relation to how many principal components should be retained to effectively represent the original data set. Rencher (2002) proposed some guidelines which are explained below:

- Hold components able to sufficiently explain a specific percentage of the original data variance, for example, 80%.
- Hold components that the eigenvalues are larger than the average of eigenvalues $\sum_{i=1}^{p} \lambda_i / p$. For the correlation matrix, the average is 1.
- Utilize the scree plot, which shows λ_i versus i, to distinguish the "large" eigenvalues to the "small" eigenvalues.
- Test the significance of the "larger" eigenvalues.

Johnson and Wichern (2007) state that there is no definitive method to determine how many components to retain in the analysis. However, some things must be taken into consideration are the amount of variance explained, eigenvalues size and interpretation of the principal components of the subject discussed. The authors also state that the scree plot is a useful visual method. Furthermore, the authors suggest retaining the principal components that are able to explain a proportion of at least $1/p$ of the total variance. Johnson and Winchern (2007) have emphasized that there is no definitive rule regarding how many principal components to be retained in the study. It is recommended that a combination of techniques mentioned above or even multiple analyses be considered for different amounts of principal components.

3.2.4 Interpretation of the principal components

Note that the principal components generated by the matrix **R** are not compatible with those obtained by the matrix **S**. In cases that the variance between the original variables have significant discrepancy, the matrix **R** can provide better results. For example, if a variable displays a much higher variance than others in the original data set, this variable will dominate the first principal component.

3.2.5 Rotation

The principal components are initially obtained by the axes rotation in order to align with the natural variability of the system, in which new variables become uncorrelated and reflect the direction of maximum variance. Figure 3.5 illustrates the rotation imposed on the axes composed by the original variables (y_1 and y_2) to obtain the principal components (z_1 and z_2) based on Rencher's (2002) analysis. Note that the line formed by the major axis seems to be a regression line (Figure 3.6). The perpendicular distance from any point to this line is minimized rather than simply minimizing the vertical distance.

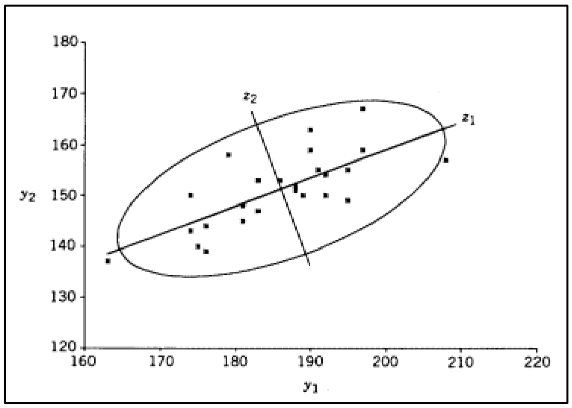


Figure 3.5: Principal component transformation for the sons data. (Source: Rencher, 2002)

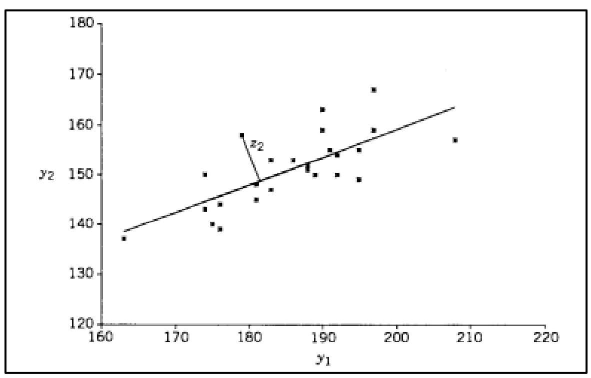


Figure 3.6: The first principal component as a perpendicular regression line. (Source: Rencher, 2002)

3.2.6 Correlation between original variables and principal components

Denote the correlation between the i^{th} variable y_i and j^{th} principal component z_j by $r_{y_i z_j}$. Since the vectors z_j are orthogonal, the relationship can be written as a joint quadratic correlation as defined in Equation (3.12):

$$r_{y_i z_1}^2 + r_{y_i z_2}^2 + \cdots + r_{y_i z_k}^2 = R_{y_i|z_1,\ldots,z_k}^2 \tag{3.12}$$

Where, k is the number of components retained and $R_{y_i|z_1,\ldots,z_k}^2$ is the multiple squared correlation (or coefficient of determination) of an y_i given the z_j. Note that an inverse analysis from $R_{z_i|y_1,\ldots,y_k}^2$ would be inconclusive because of multi-collinearity present in the data set of the original variables. A recommended analysis by Rencher (2002) interprets the coefficients obtained from the extracted eigenvectors of the matrix **R** or **S**.

3.3 DEA-PCA formulation

Zhu (1998) suggested that the principal component analysis could be applied to 'output divided by input' ratios as a complementary approach to DEA. The idea of combining DEA and PCA methodologies to achieve dimension reduction was developed independently by Ueda and Hoshiai (1997) and Adler and Golany (2001, 2002). These papers suggest that the variables can be divided into groups, based on their logical composition with respect to the production process, and then replaced with principal components representing each group separately. If most of the population variance can be attributed to the first few components, then they can replace the original variables with minimal loss of information. Let the random vector $\mathbf{Y} = [\mathbf{Y}_1, \mathbf{Y}_2, \ldots, \mathbf{Y}_q]$ (in our case the original inputs or outputs chosen to be aggregated) possess the covariance matrix

$\boldsymbol{\Sigma}$ with eigenvalues $\lambda_1 \geq \lambda_{2\geq} \ldots \geq \lambda_q \geq 0$ and normalized eigenvectors $\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_q$. The new variables, commonly known as principal components, are weighted sums of the original data which are represented by the linear combination in Equation (3.13).

$$
\begin{aligned}
&\mathbf{Y}_{PC_i} = \mathbf{e}_i'\mathbf{Y} \\
&Var\left(\mathbf{Y}_{PC_i}\right) = \mathbf{e}_i'\mathbf{Y}\mathbf{e}_i = \boldsymbol{\lambda}_i \\
&Cov\left(\mathbf{Y}_{PC_i}, \mathbf{Y}_{PC_k}\right) = \mathbf{e}_i'\mathbf{Y}\mathbf{e}_k = 0, \quad i = 1,2,\ldots,q, k = 1,2,\ldots,q, \quad i \neq k
\end{aligned}
\tag{3.13}
$$

The principal components, $\mathbf{Y}_{PC1}$, $\mathbf{Y}_{PC2}$,..., $\mathbf{Y}_{PCq}$, are the uncorrelated linear combinations ranked by their variances in descending order. The complete set of principal components is as large as the original set of variables. $\mathbf{E}_y$ is the matrix of all $\mathbf{e}_i$ whose dimensions drop from q *x* q to h *x* q, as principal components are dropped ($\mathbf{Y}_{pc}$ becomes an h *x* n matrix). Principal components can be used to replace all the inputs and/or outputs simultaneously or as specified groups of variables with a common theme. Thus linear program in Equation (3.14) refers to both the original data and principal components in order to present a generalized formulation (Adler and Yazhemsky, 2010).

$$
\begin{aligned}
e_o = \max \quad & \mathbf{U}_o'\mathbf{O}_o^a + \mathbf{U}_{pc}'\mathbf{O}_{pc}^a \\
s.t. \quad & \mathbf{V}_o'\mathbf{I}_o^a + \mathbf{V}_{pc}'\mathbf{I}_{pc}^a = 1 \\
& \mathbf{V}_o'\mathbf{I}_o^a + \mathbf{V}_{pc}'\mathbf{I}_{pc}^a - \mathbf{U}_o'\mathbf{O}_o^a - \mathbf{U}_{pc}'\mathbf{O}_{pc}^a \geq \mathbf{0} \\
& \mathbf{V}_o \geq \mathbf{0} \\
& \mathbf{U}_o \geq \mathbf{0} \\
& \mathbf{V}_{pc}'\mathbf{E}_i \geq \mathbf{0} \\
& \mathbf{U}_{pc}'\mathbf{E}_o \geq \mathbf{0} \\
& \mathbf{V}_{pc} \text{ and } \mathbf{U}_{pc} \text{ are free}
\end{aligned}
\tag{3.14}
$$

Subscript "o" is the index of original variables and "pc" is the index of principal components; $\mathbf{I}_{pc}$ represents an m x n input matrix; $\mathbf{O}_{pc}$ an r x n output matrix; $\mathbf{I}^{a}$ and $\mathbf{O}^{a}$ input and output column vectors for DMU_a respectively. V and U are multipliers for inputs and outputs.

Using principal components in place of original data does not affect the properties of the DEA models. Principal components represent the selection of a new coordinate system obtained by rotating the original system with $x_1,..., x_q$ as the coordinate axes rather than the parallel translation of the coordinate system. Thus PCA–DEA may be applied to all basic DEA models despite their lack of translation or units invariance. The disadvantage of PCA–DEA is that the data must be transformed and then, once results are obtained, it must be transformed back to the original form in order to find the targets for improvement. The results obtained from DEA with respect to each DMU reflect its position within the production possibility set relative to the efficient section of the boundary. The imposition of weights restrictions in DEA will render parts of the efficient boundary of the production possibility set no longer efficient.

Allen *et. al.,* (1997) and Dyson *et. al.,* (2001) interpreted inefficiency rating, improvement targets and efficient peers under weights restrictions. The targets and efficient peers obtained could reflect a substantial change in the current mix of input–output levels of the inefficient DMUs. A similar phenomenon occurs under the PCA–DEA formulation (as a result of the free sign in PCA). However, problems related to discrimination often arise. In extreme cases, the majority of DMUs may prove efficient, which means that there is a need for a trade-off between complete DEA information and the need to improve discrimination. It may be reasonable to argue that a decrease in one input accompanied by an increase in another input may well lead to a more efficient DMU. PCA–DEA affects the DEA results in a similar manner to adding weight restrictions but without additional preferential information from decision makers. Dropping several principal components that generally do not explain the variance appears to reduce the edges of the frontier. Thus removing the extreme (super-efficient) DMUs is generally in line with the cone-ratio or assurance region constraints.

3.4 DEA Approach Applied to Negotiate Reimbursement Plans in Healthcare Systems - Detailed procedure

The stepwise procedure, proposed by Feng and Antony (2010), presented in Figure (3.7) was used as a roadmap for Six Sigma practitioners to implement their DEA-enhanced projects. The procedure can also be utilized for Six Sigma Black Belts projects. This detailed procedure is adapted to negotiate reimbursement plans in healthcare systems in this manuscript. The Six Sigma DMAIC (Define, Measure, Analyze, Improve, Control) roadmap is utilized to illustrate the development of the DEA combined with PCA to determine the most appropriate reimbursement plan that healthcare facility can negotiate with insurance companies based on reduction of PACs. If the provider decides to apply a specific reimbursement model, the practitioner must perform DMAIC phases; otherwise, DMAC phases are sufficient to rank and to identify which payment model is the best alternative based on PACs. Figure (3.8) shows how to perform the step A6 in which the practitioner have to apply an appropriate DEA model to obtain efficiency scores for DMUs.

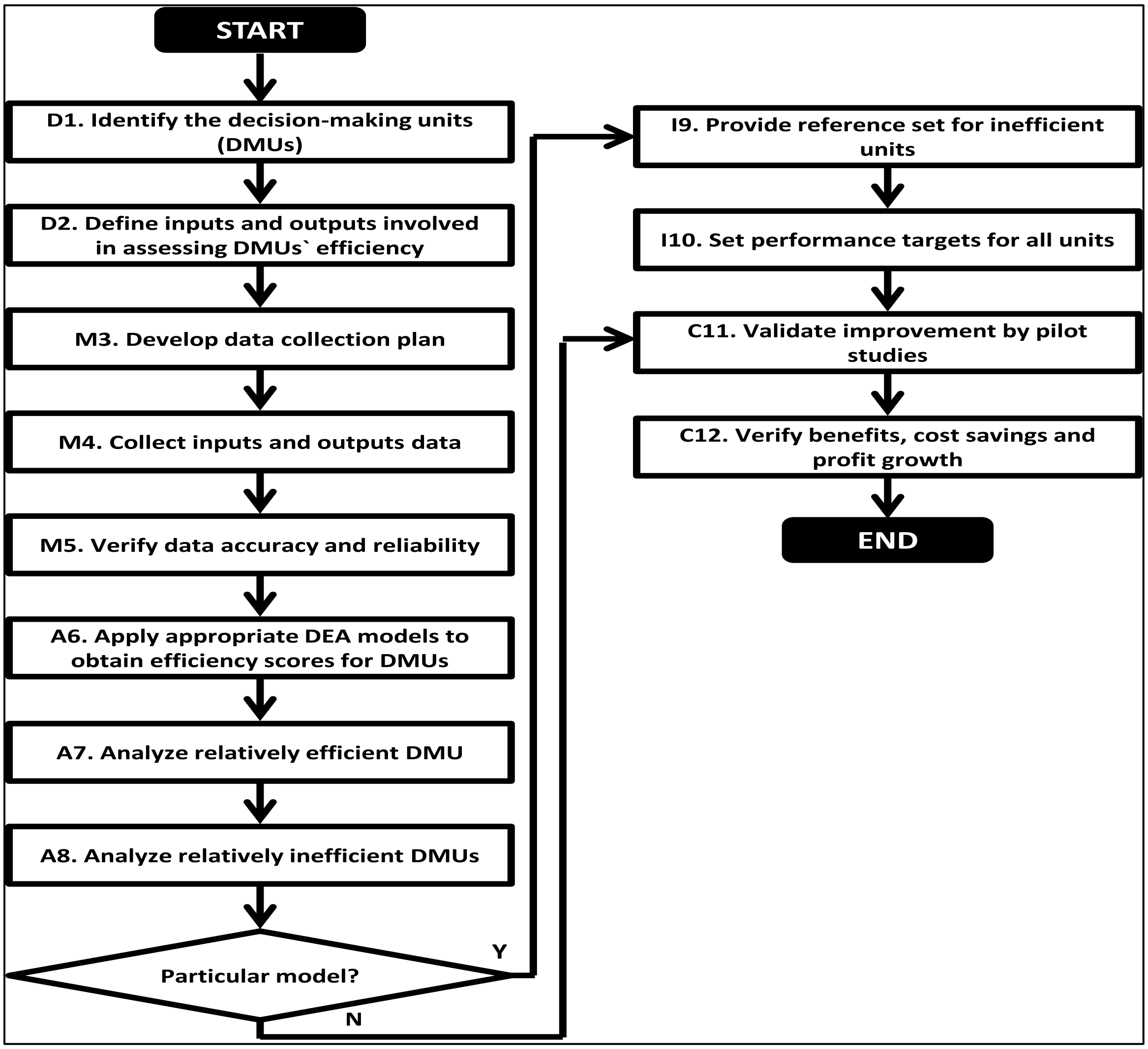


Figure 3.7: Stepwise procedure to apply DEA-DMAIC roadmap as an add tool to negotiate reimbursement plans in healthcare systems (adapted from Feng and Antony, 2010).

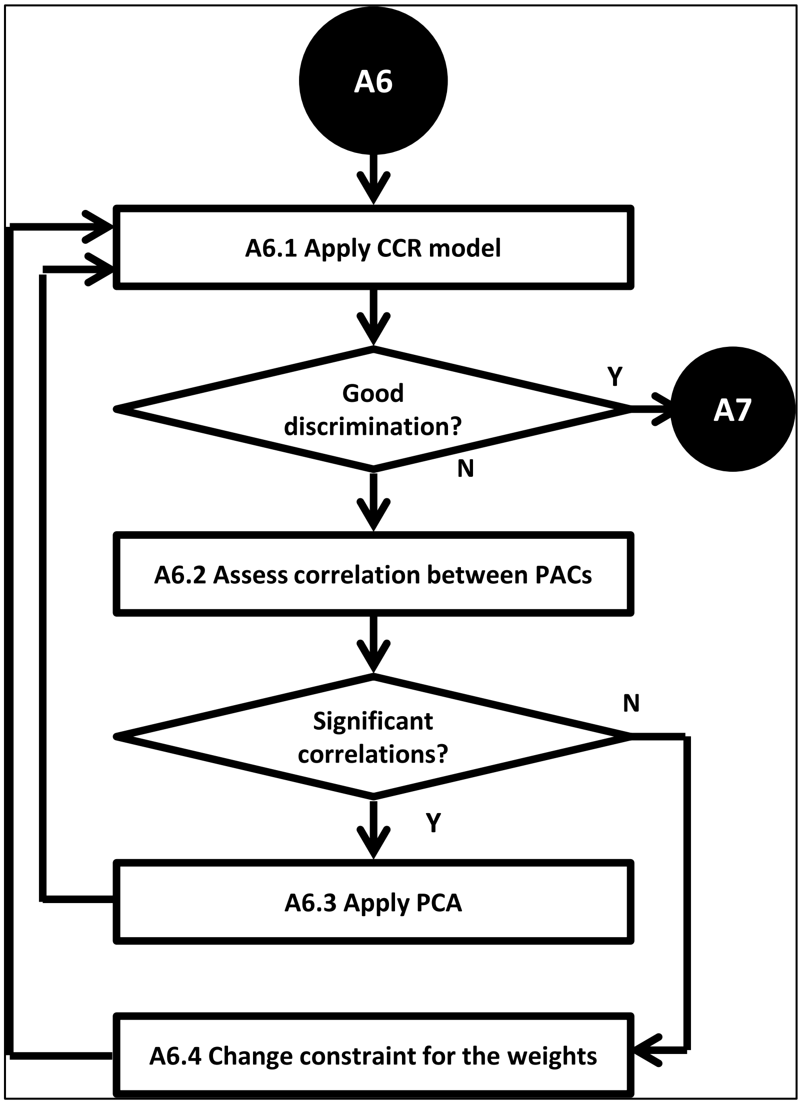


Figure 3.8: procedure to apply the DEA model for obtaining efficiency scores for DMUs

3.4.1 Define phase

The Define phase of Six Sigma DMAIC roadmap usually outlines project goals, customer deliverables, resources and the Critical-To-Quality (CTQ) characteristics. A typical DEA-enhanced Six Sigma project involves the performance/productivity/efficiency evaluation among

DMUs, which need to be clearly identified in the Define phase as well as the multiple inputs and outputs of DMUs. The DMUs in a health organization can be individual physicians, nurses, examination rooms or clinical departments. In this manuscript the DMUs are the reimbursement models. The inputs may take forms of costs, salary, time, number of physicians/nurses in a clinic and other resources. This research has considered PAC costs. The outputs of the function performed by the DMUs can be number of patients or number of severe cases. In this manuscript the output was the cost savings associated to PACs.

There are six different DMUs used in the research as described in Chapter 3. The DMUs in my research are six types of payment models grouped into three categories: Fee-for-service, PROMETHEUS and Bundled (Model 2, Model 3, Model 4 and Model 3+4), will be considered to build a strategic optimization model. There are

The variables to be considered are inpatient procedural (AMI, Pneumonia, and Stroke) and inpatient medical (Knee, Hip, BARI, COLON, and CABG). The input from these variables consists of cost of Typical Episode, PAC professional, PAC treatment (PAC Rx), PAC readmission and Added burden. And the output is 10% of sum of PAC professional, PAC treatment, PAC readmission and Added burden. Output can be more than 10%, which is mainly dependent in how much hospital can save.

3.4.2 Measure phase

The Measure phase of the Six Sigma DMAIC roadmap quantifies and benchmarks the process based on actual data. Six Sigma requires that data be collected accurately and reliably.

Otherwise, ‘garbage in and garbage out’ phenomena would happen regardless of the model utilized for analysis. Therefore, this phase involves developing a collection plan, collecting data, and verifying data accuracy and reliability. For the reimbursement models considered in this manuscript the data is usually deterministic, rather than random variables. This data is based on observations from past decisions (inputs) and resultant outputs (Feng and Antony, 2010).

The data used in the model is from Healthcare Incentive Improvement Institute, Inc. Their website www.hci3.org has data for public use. The data for the research is from CMMI Bundled Payment Pilot Analysis Package (a national database with over 4.7 million people covered).

3.4.3 Analyze phase

The Analyze phase of the Six Sigma DMAIC roadmap intends to apply the DEA model developed in this manuscript to select the best reimbursement plan. This analysis is performed at three different levels:

1. Individual analyses for each DRGs;
2. Analyses of DRG groups;
3. Aggregated analysis.

3.4.4 Improve phase

The Improve phase of the Six Sigma DMAIC roadmap determines the best solution using optimization approaches. In this manuscript, improve phase will be performed only if the provider decides to select their reimbursement model for very specific types of DRGs. There is a chance that selected model not being considered efficient; therefore, DEA can show which PAC should be reduced to make the selected model more efficient.

3.4.5 Control phase

The Control phase of the Six Sigma DMAIC roadmap checks the process for statistically significance before/after the improvement. Controls need to be implemented to hold the gains, which involve monitoring DMUs' performance, developing corrective procedures and training people who run the process.

CHAPTER 4

RESULTS AND DISCUSSION

Section 1

There are six different DMUs used in the research. The DMUs in my research are six types of payment models grouped into three categories: Fee-for-service, PROMETHEUS and Bundled (Model 2, Model 3, Model 4 and Model 3+4), will be considered to build a strategic optimization model. There are

The variables to be considered are inpatient procedural (AMI, Pneumonia, and Stroke) and inpatient medical (Knee, Hip, BARI, COLON, and CABG). The input from these variables consists of cost of Typical Episode, PAC professional, PAC treatment (PAC Rx), PAC readmission and Added burden. And the output is 10% of sum of PAC professional, PAC treatment, PAC readmission and Added burden. Output can be more than 10%, which is mainly dependent in how much hospital can save.

An application of the DMAIC procedure is presented in section 4.1 for a single DRG, AMI. Next, the analyses for the remaining DRGs as well as an overall assessment are shown in section 4.2.

4.1 Application for a single DRG

4.1.1 Define phase

There are six different DMUs used in the research. These DMUs, six types of payment models grouped into three categories: Fee-for-service, PROMETHEUS and Bundled (Model 2, Model 3, Model 4 and Model 3+4), will be considered to build a strategic optimization model.

The input from these variables consists of cost of Typical Episode, PAC professional, PAC treatment (PAC Rx), PAC readmission and Added burden. And the output is 10% of sum of PAC professional, PAC treatment, PAC readmission and Added burden. Output can be more than 10%, which is mainly dependent on how much hospital can save.

4.1.2 Measure phase

The data used in the model is a publicly available data from www.hci3.org. The Prometheus playbook available on the website has data that comes from their developmental database (a national database with over 4.7 million covered lives). The numbers for the optimization model were derived from the playbook.

4.1.3 Analyze phase

To assess the relative efficiency, the input-oriented CCR model in Equation (3.3) was specified for this problem with five inputs and one output. The linear programming model was easily solved using Excel Solver for $j_0 = 1, ..., 6$. Each time the model was suitably modified for the unit being assessed. Figure (4.1) shows the model being executed by the DMU, PROMETHEUS. The obtained optimal values for μ_r , υ_i and e_0 provide information on the weights for inputs and outputs and the DEA score for the respective unit. This information can be further used to rank DEA scores, identify the reference set and set the performance target.

Model/ AMI	Inputs					Output					Constraints					
	Typical Episode	PAC Professional	PAC Rx	PAC IP Readdmission	Added Burden	Savings		Sum Inputs	Sum Outputs	e_0	1			2		
FFS	$24,467	$2,551	$151	$17,703	$7,019	0		1.00	0.00	0%	(1.00)	<=	0	1.00	=	1
PROMETHEUS	$24,467	$2,551	$151	$17,703	$7,019	$2,742.43		1.00	1.00	100%	(0.00)	<=	0	1.00	=	1
Model 2	$22,232	$1,020	$125	$6,242.94	$3,017.42	$1,040.49		0.63	0.38	60%	(0.25)	<=	0	0.63	=	1
Model 3	$18,295	$1,410	$173	$8,631.36	$4,171.82	$1,438.56		0.63	0.52	83%	(0.11)	<=	0	0.63	=	1
Model 4	$22,382	$1,256	$154	$7,687.98	$3,715.86	$1,281.33		0.68	0.47	69%	(0.21)	<=	0	0.68	=	1
Model 3+4	$42,374	$2,665	$326	$16,319	$7,888	$2,719.89		1.34	0.99	74%	(0.35)	<=	0	1.34	=	1
Weights	1.93E-05	1.9271E-05	1.9E-05	1.9271E-05	1.93E-05	0.000365										
>=																
1.9271E-05	0.2	0.2	0.2	0.2	0.2	1										

Figure 4.1: Excel solver of CCR model being solved for the DMU PROMETHEUS

The optimal value of e_0 indicates the DEA score for each unit, which is shown in Figure 4.1. If the DEA score equals to 100% and the constraints 1 and 2 are attended, the unit being assessed is said to be efficient. Therefore, PROMETHEUS was the unique DMU considered efficient when analyzing the dataset for the DRG, AMI.

4.1.4 Improve phase

The results from the DEA's solution can be interpreted to provide reference sets for inefficient units and to set performance targets for all units. However, these steps are required in situations where the provider has already decided to implement a particular reimbursement plan and the selected plan was considered inefficient. For instance, a particular hospital has decided to implement "Model 3+4". Figure 4.2 show that the efficiency was assessed in 74% and the reference set for this DMU is the DMU PROMETHEUS (constraint 1 for DMU PROMETHEUS was equal to zero, or $\sum_r u_r y_{rj} = \sum_i v_i x_{ij}$). Therefore, performance targets for the DMU Model 3+4 could be set, based on reducing PACs according to the results for the efficient DMU in CCR model analysis.

Model/ AMI	Inputs					Output					Constraints					
	Typical Episode	PAC Professional	PAC Rx	PAC IP Readdmission	Added Burden	Savings		Sum Inputs	Sum Outputs	e_0	1			2		
FFS	$24,467	$2,551	$151	$17,703	$7,019	0		0.75	0.00	0%	(0.75)	<=	0	0.75	=	1
PROMETHEUS	$24,467	$2,551	$151	$17,703	$7,019	$2,742.43		0.75	0.75	100%	(0.00)	<=	0	0.75	=	1
Model 2	$22,232	$1,020	$125	$6,242.94	$3,017.42	$1,040.49		0.47	0.28	60%	(0.19)	<=	0	0.47	=	1
Model 3	$18,295	$1,410	$173	$8,631.36	$4,171.82	$1,438.56		0.47	0.39	83%	(0.08)	<=	0	0.47	=	1
Model 4	$22,382	$1,256	$154	$7,687.98	$3,715.86	$1,281.33		0.51	0.35	69%	(0.16)	<=	0	0.51	=	1
Model 3+4	$42,374	$2,665	$326	$16,319	$7,888	$2,719.89		1.00	0.74	74%	(0.26)	<=	0	1.00	=	1
Weights	1.44E-05	1.43735E-05	1.4E-05	1.43735E-05	1.44E-05	0.000272										
>=																
1.9271E-05	0.2	0.2	0.2	0.2	0.2	1										

Figure 4.2: Excel solver of CCR model being solved for the DMU Model 3+4

4.1.5 Control phase

Validation of the savings obtained from adoption of a particular model must be assessed in order to confirm that the model selected was the benchmark. The analyst can also monitor PACs using statistical control charts, which have been widely used in healthcare applications for monitoring and improvement of hospital performance. PACs in healthcare systems can be compared to defects in manufacturing context. Therefore, after identifying the best reimbursement model, the hospital can track PACs in its processes to achieve higher benefits, cost savings and profit growth.

4.2 Remaining DRGs and overall analyses

The summarized results are presented in Table 4.2 and in Figure 4.3. Table is color coded for easier understanding, where red color means least efficient, green the most efficient model and yellow somewhere in the middle. As expected FFS is the least efficient model among all the models of reimbursement since providers do not save anything. The Table 4.2 below has an empty box for Model 4 in DRG BARI column, which means episode of BARI does not extend long and so there is no data available to see how much was spent on it and how much could be saved. If provider can negotiate for Model 4 reimbursement model for BARI, it would be 100% saving for them!

From Table 4.2 and Figure 4.3 it can be deduced that PROMETHEUS is the most efficient model for most of the DRGs considered in the study. Model 3 and Model 4 are most efficient for COLON and CABG respectively. In case of Pneumonia and Hip replacement, Model 4 along with PROMETHEUS is the most efficient model of reimbursement.

Table 4.2: Summary of Relative Efficiency of DMUs for all DRGs and Sum of all DRGs evaluated using CCR-DEA Optimization Model

CCR-DEA	All	AMI	Pneumonia	Stroke	Knee	Hip	BARI	Colon	CABG
FFS	0%	0%	0%	0%	0%	0%	0%	0%	0%
PROMETHEUS	100%	100%	100%	100%	100%	100%	100%	88%	55%
Model 2	72%	60%	75%	72%	68%	83%	70%	100%	26%
Model 3	97%	83%	80%	34%	88%	74%	66%	78%	100%
Model 4	66%	69%	100%	21%	50%	100%	#DIV/0!	89%	66%
Model 3+4	82%	74%	35%	21%	88%	48%	33%	67%	72%

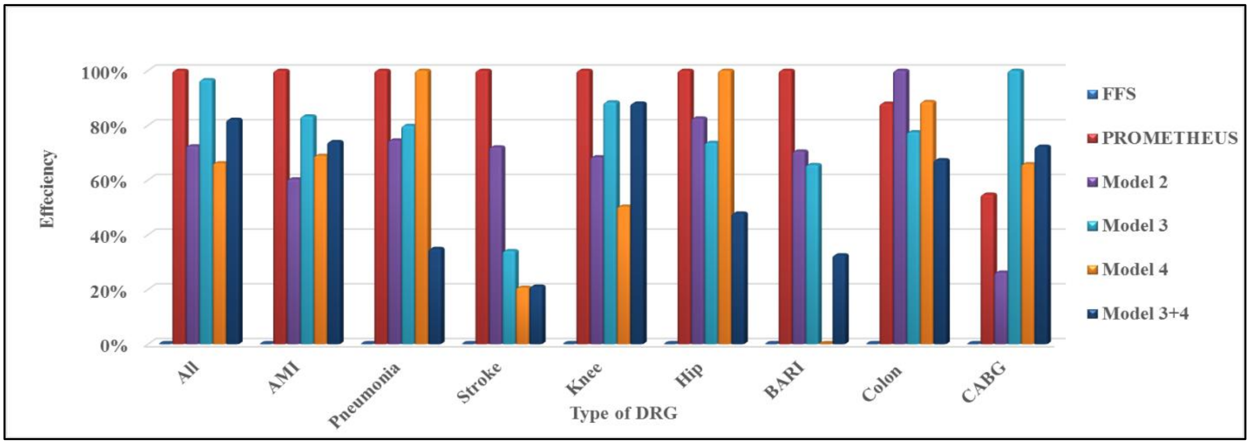


Figure 4.3: Relative Efficiency of DMUs for all DRGs and Sum of all DRGs evaluated using CCR-DEA Optimization Model

Section 2

Firstly, section 4.3 shows an application to a group of DRGs using a PCA-DEA approach. Some steps are described more briefly due to similarity to previous section. As long as the problem is the same, only a different perspective is introduced to determine a new point of view when evaluating group of DRGs, in this case, medical inpatient. Secondly, result analyses are extended to procedural group of DRGs and an overall assessment in section 4.4.

4.3 Application to a group of DRGs

4.1.1 Define phase

As mentioned in section 4.1, DMUs assessed in this manuscript are: Fee-for-service, PROMETHEUS and Bundled (Model 2, Model 3, Model 4 and Model 3+4). The input from these variables consists of cost of Typical Episode, PAC professional, PAC treatment (PAC Rx), PAC readmission and Added burden. And the output is 10% of sum of PAC professional, PAC treatment, PAC readmission and Added burden. Output can be more than 10%, which is mainly dependent in how much hospital can save.

4.1.2 Measure phase

The data used in the model is a publicly available data from www.hci3.org. The Prometheus playbook available on the website has data that comes from their developmental database (a national database with over 4.7 million covered lives). The numbers for the optimization model were derived from the playbook. Medical inpatient was the group of DRGs analyzed in this section.

4.1.3 Analyze phase

To assess the relative efficiency, the input-oriented CCR model in Equation 3.3 was specified for this problem with five inputs and one output. The linear programming model was easily solved using Excel Solver for $j_0 = 1, ..., 6$. Each time the model was suitably modified for the unit being assessed. Figure 4.4 shows the model being executed for the DMU, PROMETHEUS. As can be seen in Table 4.2, the discrimination between DMUs was not satisfactory to identify which DMU was the most efficient. As a solution, the correlation structure between PACs was evaluated to determine the feasibility of using PCA as a reduction strategy of inputs, and consequently, improvement of the discrimination in this analysis. Figure 4.5 shows that most of the correlations between PACs were significant with 0.05 of significance level.

Model/ AMI	Inputs					Output					Constraints					
	Typical Episode	PAC Professional	PAC Rx	PAC IP Readdmission	Added Burden	Savings		Sum Inputs	Sum Outputs	e_0	1			2		
FFS	$44,144	$5,892	$548	$62,399	$24,831	0		$1	$0	0%	-$1	<=	0	$1	=	1
PROMETHEUS	$44,144	$5,892	$548	$62,399	$24,831	$9,366.88		$1	$1	100%	$0	<=	0	$1	=	1
Model 2	$42,798	$2,431	$296	$14,149	$6,005	$2,288.07		$0	$0	98%	$0	<=	0	$0	=	1
Model 3	$28,815	$2,588	$316	$15,236	$6,650	$2,478.97		$0	$0	100%	$0	<=	0	$0	=	1
Model 4	$42,951	$1,401	$253	$8,496	$4,035	$1,418.48		$0	$0	100%	$0	<=	0	$0	=	1
Model 3+4	$71,765	$3,989	$569	$23,732	$10,685	$3,897		$0	$0	100%	$0	<=	0	$0	=	1
Weights	1.68E-07	1.51924E-05	0	1.44729E-05	0	0.000107										
>=																
0	0.005615	0.509251084	0	0.485133683	0	1										

Figure 4.4: Excel solver of CCR model being solved for the DMU PROMETHEUS

	PAC Professional	PAC Rx	PAC IP Readdmiss
PAC Rx	0.905		
	0.013		
PAC IP Readdmiss	0.968	0.790	
	0.002	0.061	
Added Burden	0.975	0.811	0.999
	0.001	0.050	0.000

Cell Contents: Pearson correlation
P-Value

Figure 4.5: Correlation structure between PACs

Figure 4.6 presents the principal component analysis for PACs of medical inpatients based on the covariance matrix. As emphasized in Figure 4.6, only PC_1 is enough to explain the variability of the original data set. Therefore, PACs were replaced by the scores of principal components and the CCR model was executed over again. The results in Table 4.2 determine that the new model could distinguish better efficient from inefficient DMUs.

Eigenanalysis of the Covariance Matrix

Eigenvalue	706899883	298245	28794	98
Proportion	1.000	0.000	0.000	0.000
Cumulative	1.000	1.000	1.000	1.000

Variable	PC1	PC2	PC3	PC4
PAC Professional	0.069	0.835	0.542	-0.070
PAC Rx	0.004	0.159	-0.120	0.980
PAC IP Readdmission	0.931	-0.243	0.264	0.068
Added Burden	0.359	0.468	-0.789	-0.174

Fig 4.6: Principal component analysis for PACs

Model/ Procedural	Input			Out put					Constraints					
		Typical Episode	PC 1	0		Sum Inputs	Sum Outputs	Effeciency	1			2		
FFS		44144	67402	0		1	0	0%	-1	<=	0	1	=	1
PROMETHEU		44144	67402	6740		1	1	100%	0	<=	0	1	=	1
Model 2		42798	15494	1549		1	0	44%	0	<=	0	1	=	1
Model 3		28815	16748	1675		0	0	61%	0	<=	0	0	=	1
Model 4		42951	9454	945		0	0	30%	0	<=	0	0	=	1
Model 3+4		71765	26202	2620		1	0	44%	0	<=	0	1	=	1
Weights		8.96E-06	8.96E-06	1.48E-04										
>=														
8.96E-06		0.5	0.5	1.0										

Figure 4.7: Relative Efficiency of Model 4 Reimbursement Model for Procedural DRGs evaluated using PCA-DEA Optimization model

4.1.4 Improve phase

The results from the DEA's solution can be interpreted to provide reference sets for inefficient units and to set performance targets for all units. Since the aim of this study is not related to a particular reimbursement model, the improve phase was not performed for this dataset.

4.1.5 Control phase

Validation of the savings obtained from adoption of a particular model must be assessed in order to confirm that the model selected was the benchmark. The analyst can also monitor PACs using statistical control charts, which have been widely used in healthcare applications for monitoring and improvement of hospital performance. PACs in healthcare systems can be compared to defects in manufacturing context. Using PCA, only one vector (PC_1) represents the entire PAC dataset; thereby, an alternative control system may be implemented based on PC_1 analysis.

4.4 Application to the groups procedural and medical inpatient and overall analyses

The PCA-DEA optimization model was run for both procedural and medical inpatients group of DRGs as well as for sum of all the DRGs. The summary of results is presented in Table 4.2 and Figure 4.8.

Table 4.2: Summary of Relative Efficiency of DMUs for Procedural and Medical DRGs and Sum of all DRGs evaluated using PCA-DEA Optimization Model

PCA-DEA	All	Procedural	Medical
FFS	0%	0%	0%
PROMETHEUS	100%	100%	83%
Model 2	60%	44%	60%
Model 3	96%	61%	100%
Model 4	61%	30%	71%
Model 3+4	79%	44%	86%

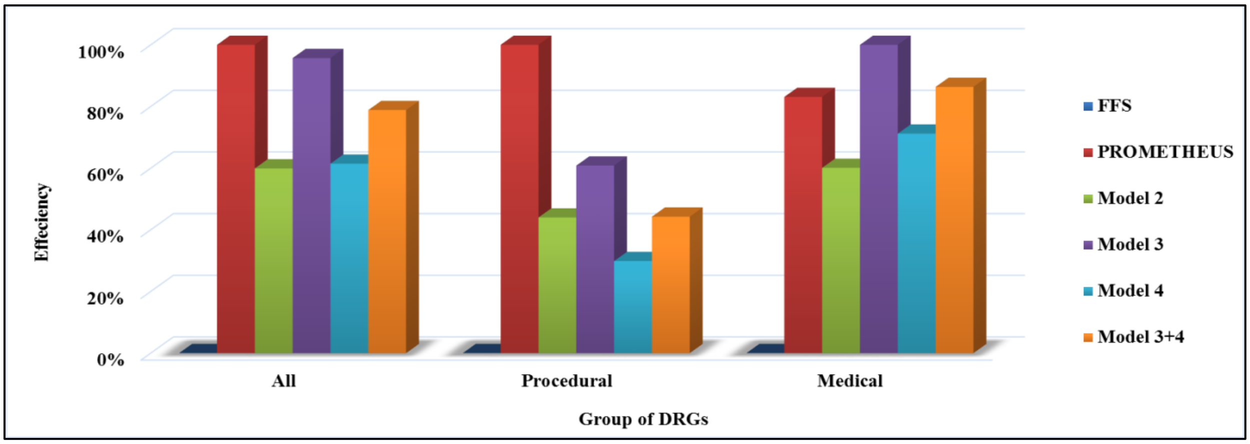


Figure 4.8: Summary of Relative Efficiency of DMUs for Procedural and Medical DRGs and Sum of all DRGs evaluated using PCA-DEA Optimization Model

CHAPTER 5

CONCLUSION

The PPACA law or the Obama care aims at improving the quality and increasing the affordability of health insurance. The law also aims to reduce escalating healthcare costs and improve healthcare outcomes by moving from current quantity driven system to more quality driven system. To improve accountability in the delivery of healthcare, Medicare & Medicaid and private insurers have developed several reimbursement plans/models as mentioned in Chapter 1.

Payment is not the only factor influencing the behavior of provider and patient, but its importance has been recognized. The importance of aligning payment policies with quality improvement has been emphasized in *"Crossing the quality chasm: A new health system for the 21st century"* (Institute of Medicine, 2001). The committee has called for all the purchasers to come together and look at their payment policies to removes the barriers that impede improvement. They have mentioned the importance of stronger incentives in quality improvement.

According to Jencks *et. al.,* (2009), Medicare readmissions because are frequent cost a lot to the overall healthcare system, including to the hospitals. To address this situation policy makers are increasingly interested in solving the problem by pushing for new reimbursement plans. These reimbursement and environmental changes combined together have put great pressure on financial performance of hospitals. In some cases the stress has been so much so that it resulted in closure of the hospital.

One of the critical factors in financial success of all industries is how well it manages its costs. The introduction of prospective payment systems and managed competition, has diminished the importance of cost management as a single critical factor. “Reimbursement changes create the need to maintain and stabilize revenue streams, and revenue factors are emerging as key corollaries to hospital financial success.”

In such a dynamic environment, where hospitals are closing or are being bought by bigger hospitals or insurance companies, it becomes important for not only their survival but also their financial success that they have a strategy while negotiation for reimbursement contracts with insurance companies. The DEA optimization model that we have built can serve both as an optimization model as well as a strategic tool for providers’ success, by aligning the incoming patient population with the possible financial incentives.

All the different reimbursement models in the research were analyzed using the publically available data from data from HCI3. As promised at the beginning of the research, our model has the ability not only to assess which reimbursement model works best for which DRG, but also capable of ranking in their order of efficiency. We have also analyzed different reimbursement models based on different groups of DRGs, namely procedural and medical inpatient. The results are different from when analyzed for each DRG and all the DRGs together.

One of the disadvantages of CCR-DEA optimization model is its poor resolution among DMUs. Optimization using PCA along with DEA provides better resolution between reimbursement models that seem to have similar relative efficiencies, which can help in quick decision making. From our literature survey and to the best of our knowledge, PCA has not been used before in conjunction with DEA in healthcare settings.

Our results show DEA can be serve as a negotiation tool in healthcare negotiations. DEA when combined with PCA has more power to discriminate among different DMUs, as seen in Figure 4.8, which can help hospitals to choose from various closely efficient reimbursement models. Based on the results from our optimization model, the DRGs that are more profitable or more efficient or have more number of patients being treated, the providers can decide about their future investment. Figure 3.7 explains stepwise procedure to apply DEA-DMAIC roadmap as an add tool to negotiate reimbursement plans in healthcare systems.

The ability of our optimization model to analyze the efficiency of reimbursement models at so many levels gives it a potential to be a strategic tool that can help providers not only negotiate with different insurers but also provide competitive edge in the market.

Our optimization model will not only help financial health of hospitals but also force them to provide quality service to the patients as mentioned in Obama care Act.

For future research more DRGs could be included for overall optimization. DEA also has a potential to be used in clinical efficiency which affects the financial outcome of the hospitals. People behavior in different organization and how it affects their efficiency is another area of future research. DEA combined when combined with other techniques like PCA, MCDM or MAUT can provide a robust tool for calculating efficiency in almost all the fields.

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VITA

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