6-22-2020

An Assessment of the Decision-Making Units' Efficiency in Service Systems

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by

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A dissertation submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy
in
Technology Management

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Portland State University
2020

ABSTRACT

Most tools and models of performance and quality of service management are generic and do not solve complex technical systems. The critical components of the system need such tools to assess their efficiency to make a better decision about them. One of the primary objectives in the service systems is to improve the ability of efficiency, effectiveness, and sustainability of critical assets. One of the challenges with improving critical assets is the amount of major capital spending needed to upgrade a technology infrastructure with a high obsolescence rate. This along with usage and reliability issues, makes evaluating mobile cells to enhance the Quality of Services (QoS) more difficult.

This research bridges engineering and management by using a robust and objective management tool for benchmarking mobile Base Transceiver Station's (BTS) efficiency with the important radio Key Performance Indicators (KPIs) for evaluating technical efficiency. The objective of this research is to assess the cellular performance and BTS efficiency by demonstrating a robust model that is derived from multiple KPIs based on technical and financial aspects. This novel research provides a comprehensive multidimensional model for tuning the BTS's parameters, which can lead to developing a standard global mobile network KPI. The model measures the efficiency of BTSs and offers a reference set for inefficient BTSs to improve their efficiency. This creates tuning guidelines for the

network optimization engineers to improve inefficient BTSs by comparing their configurations with efficient BTSs to achieve a high level of network optimization. Thus, the benchmarking classifies the BTSs into four categories using a performance matrix, and this analysis helps the decision-makers to focus on the right area, and to identify the most critical BTSs based on best practices.

The first part of the research includes a literature review, highlights of the problem statement, research motivation, and the research focus. Data Envelopment Analysis (DEA) is employed as the main methodology to build the evaluating model, and to identify a robust multi-dimensional benchmarking model using resources allocated as inputs and multi-outputs of KPIs. The expert judgments were also used to validate the model and the results. The second stage of the model uses the principles of the Boston Consulting group's product portfolio matrix (BCG matrix) as a performance matrix approach to provide target-setting strategies. Also, the statistical and regression analyses are adopted to extract useful insights, which helps the implementation of the enhancements. The real data from a local mobile operator in North Africa is used as a case study.

Besides the analysis and the assessment of the BTSs' efficiency, a set of recommendations is provided to improve the inefficient BTSs. Moreover, the set of references from the best practice point of view for the inefficient BTSs are defined. These results give network engineers specific suggestions to improve the inefficient BTSs based on tuning parameters of best practices for peers. Finally, the scope of further research is provided along with some opportunities to enhance the model for new technology and other aspects of application areas as well as the future steps to validate the results in a real network.

DEDICATION

To my precious mother and dear father, who taught me the meaning of effort and perseverance, who brought me up with affection and love, and who with their prayers pushed me forward.

To my life partner, for whom I have the utmost respect, who still gives me unparalleled positive energy and to make a failure become a success, and to my life joy, my sweet kids (Lokman, Abdulrahman, Layan, and Razan).

To my brothers who share with me most beautiful memories, to all my family and friends who lived in my life with all friendliness and respect.

Also, I would like to express my dedication to everyone who has illuminated me with his/her knowledge or guided me by offering the right answer to my puzzling, to those who shared with me the character of life and its sorrows, whom I ask Allah to protect from every evil, to those who have waited anxiously for this moment, to those who have given me all the means of comfort to reach this educational level.

ACKNOWLEDGMENTS

First thanks to Allah Almighty, who helped me complete my Ph.D., and I ask Allah to make this research beneficial to people. I extend my sincere thanks, gratitude, appreciation, and love to those who carried the holiest message in life, to those who paved the way of knowledge, and to all my distinguished professors, and I especially appreciate and thank you:

My honorable advisor Dr. Tim Anderson for his support and guidance by advising me well; my Ph.D. committee, Dr. Charles Weber, Dr. Robert Fountain, Dr. Xiaoyu Song; and many thanks goes to the administration, faculty, and students at Portland State University.

My country, Libya, and the Ministry of Higher Education and Scientific Research who support me financially during my master's study.

My company, Almadar Aljadid who supported me with the data, my colleagues, and the expert panels for all their support and help.

Finally, I am pleased to thank all those who advised, guided, directed, or contributed with me in preparing this research by referring to the required references and resources during all of its stages.

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Acronym	Definition
AGCH	Access Grant Channel
AHP	Analytic Hierarchy Process
AM	Accessibility Model
ANP	Atrial natriuretic peptide
BCG	Boston Consulting Group
BN	Bayesian Networks
BS	Base Station
BSC	Base Station Controller
BSS	Base Station System
BTS	Base Transceiver Station
CART	Classification and Regression Trees
CM	Configuration Management
CRS	Constant Returns-to-Scale
CSSR	Call Setup Success Rate
DEA	Data Envelopment Analysis
DFA	Distribution-Free Approach
DM	Data Mining
DMT	Data Mining Techniques
DMU	Decision-Making Units
FCM	Fuzzy Cognitive Mapping
FDH	Free Disposal Hull

FM	Fault Management
GM	General Model
GSM	Global System for Mobile Communications
HDM	Hierarchical Decision Model
HO	Handover
KD	Knowledge Discovery
KDD	Knowledge Discovery Database
KDDM	Knowledge Discovery and Data Mining
KNN	K-nearest Neighbors
KPIs	Key Performance Indicators
LPTIC	Libyan Post Telecom and Information Technology Company
LTT	Libya Telecom & Technology
MADM	Multi-Attribute Decision Making
MCDA	Multiple Criteria Decision Analysis
MCDM	Multiple Criteria Decision-Making
MM	Mobility Model
MODM	Multi-Objective Decision Making
MS	Mobile Station
NN	Neural Networks
OSS	Operational Support System
PM	Performance Management
PSO	Particle Swarm Optimization
QFD	Quality Function Deployment
QoS	Quality of Service
RACH	Random Access Channel

RBS	Radio Base Station
RM	Retainability Model
RNO	Radio Network Optimization
Rx-Lev	Received Signal Level
SA	Sensitivity Analysis
SDCCH	Stand-alone Dedicated Control Channel
SFA	Stochastic Frontier Analysis
SIM	Service Integrity Model
SLA	Service Level Agreement
STS	Statistics and Traffic Measurement Subsystem
SVM	Support Vector Machine
TCH	Traffic Channel
TDMA	Time-Division Multiple Access
TFA	Thick-Frontier Approach
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TRU	Transceiver Unit
TRX	Transceiver
UA	User Administration
UMTS	Universal Mobile Telecommunications Service
VRS	Variable Returns-to-Scale

Chapter 1 Introduction

Service science is the study of service systems, which is aimed at creating a basis for systematic service innovation (Maglio and Spohrer 2008). The main goal of service science is to increase the productivity of the service industry, and to create greater quality with assessing the value of investments in services. The cellular telecom industry is a critical service industry that other industries rely on. Many daily life services are built on telecommunication mobile service availability and quality, which makes this industry critical and competitive (Wac *et al.* 2011, Caylar and Ménard 2016). Since the 1990s, the telecommunication industry, specifically the mobile sector, has become one of the fastest-growing sectors. Developing countries have been trying to keep up with these changes (Chavula 2013, Casey 2014). There has been a rapid increase in mobile subscribers which, by 2016, exceeded the world population as shown in Figure 1.1. It is imperative that the mobile operators adopt an assessment approach for service quality to respond to an increasingly competitive environment of customer satisfaction (Lee *et al.* 2001, Haider *et al.* 2009, Owusu and Duah 2018). It is also crucial for mobile operators to exhibit persistent superior performance over their competitors and adopt emerging cellular technology developments to achieve a competitive advantage and stay in the market (Khadem *et al.* 2008, Asimakopoulos and Whalley 2017, Owusu and Duah 2018).

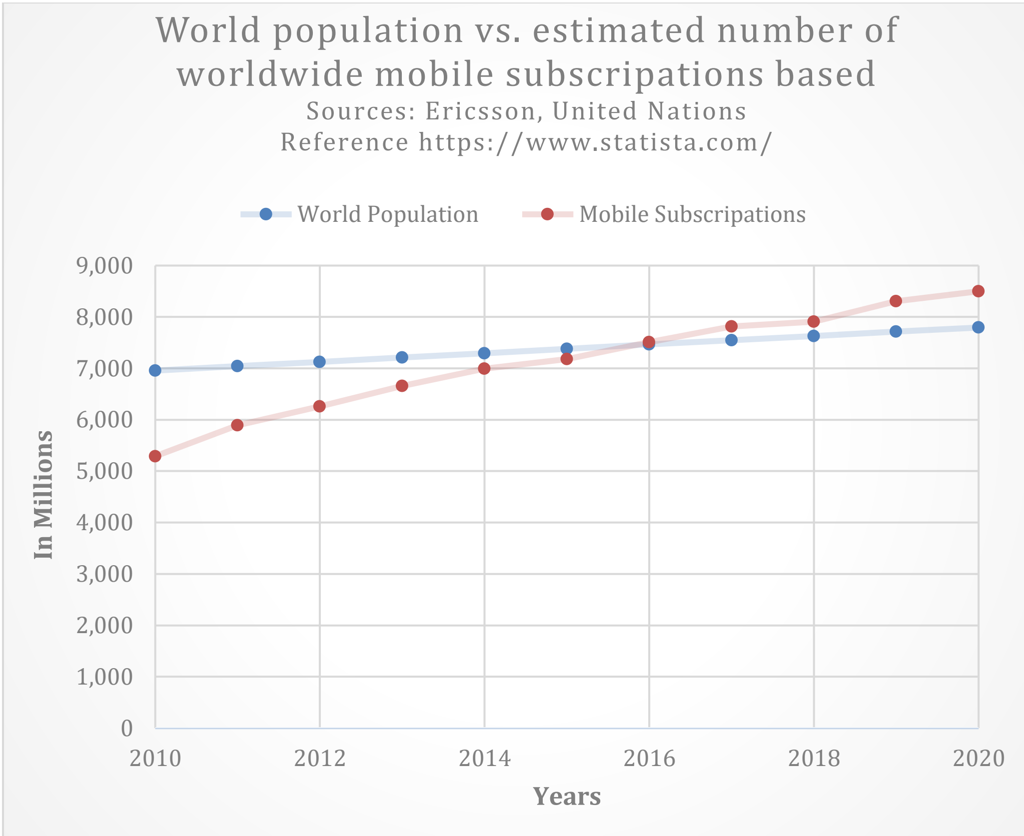


FIGURE 1.1: *MOBILE SUBSCRIPTIONS TO OUTNUMBER THE WORLD'S POPULATION*

Mobile operators face many new challenges and opportunities while they develop their technologies, and they have to be strategic to maintain customer satisfaction. One of the primary conditions for achieving high cellular services is the performance of the Base Transceiver Station (BTS). Mobile network performance and Quality of Service (QoS) are the top evaluation criteria for most customers (Kumar *et al.* 2002, Seytnazarov 2010). Therefore, considerable effort has been spent to develop the BTS to provide better services. We can increase the BTS efficiency by determining the inefficient BTS based on their performance against multiple Key Performance Indicators (KPIs) (Dabab and Anderson 2019). Performance management helps to check the performance of the network, and to look for indications that all KPIs of the individual network elements or services are performing overall QoS (Kyriazakos *et al.* 2002, Haider *et al.* 2009, Alam 2013). To improve the quality and performance of the cellular network, the Radio Network Optimization (RNO) engineers need to have the right tool to benchmark the sites' efficiency.

Thus, to provide better QoS and guarantee high network performance, it is critical for operators and providers to be able to measure the performance of the network assets. In recent years, attention has been paid to the planning, evaluation, and optimization of mobile cellular networks since the cellular technology infrastructure requires significant capital spending, given the rapid obsolescence requiring frequent upgrades. Evaluating the base station efficiency is a challenging and complicated process because the nature of the system performance depends on many KPIs. One of the primary tasks of radio engineers is to come up with an optimal configuration and to set parameters to the base stations to provide an acceptable quality of service, which is a complex task. Awada, Wegmann, and Viering highlighted one of the issues that the mobile optimization engineer faces as "finding the optimal parameter setting for each base station that maximizes a predefined performance metric is a difficult problem." (Awada *et al.* 2011).

Due to the increase in competition, the importance of quality of service and performance evaluation to improve the provider's customer satisfaction should be taken into consideration more than ever. Therefore, several studies and approaches have evaluated the relative performance and efficiency of production units in various sectors. Since the 1960s, Multiple Criteria Decision Analysis (MCDA) and Multiple Criteria Decision-Making (MCDM) has been an active research subcategory, and has produced many theoretical and applied papers and books. These tools have been used in a variety of fields such as business management, government administration, engineering management, scientific management, and economics. Moreover, the term "knowledge discovery in databases" appeared for the first time in the 1980s to point out that knowledge is the product of a discovery process navigable by data. Discovery or extraction of knowledge in large datasets is made possible through Data Mining (DM) methods, which help in three areas of discovery: finding the hidden patterns, predicting or forecasting future information, and forensic or investigation of data elements (Rygielski *et al.* 2002). From the marketing strategies perspective, data mining can be applied to three main areas of applications: profiling analysis, deviation analysis, and trend analysis (Shaw *et al.* 2001).

Qiang Yang found that many techniques are designed for individual problems, and there is no unifying theory (Yang and Wu 2006). It is useful to understand why some techniques are performing better than others, and to compare them from a research-needs perspective to determine the best method to use on a specific problem. The nature of the problem in this research requires a method that considers a variety of factors, and that builds the evaluating model using multiple inputs and multiple outputs. Therefore, the Data Envelopment Analysis (DEA) is employed as the methodology because it meets this purpose, and can be used to generate a composite of efficiency, productivity, performance, and benchmarking measures. Mobile providers measure the BTS efficiency through a variety of KPIs, and they compare the network's KPIs with the standard KPIs of the vendor. The DEA technique has been used in the telecommunication and mobile sector to evaluate a firm's efficiency either by comparing it with other firms or from assessing the firm at the country level. In 2010, a study was conducted to evaluate the efficiency of the BTS for one of the Iranian provinces using DEA (Taghizadeh and Ebrahimi 2010). However, the model was built based on using the site costs as inputs and traffic-measurement KPIs as outputs, which has limitations.

Businesses can be efficient, but not effective; similarly, they can be effective and not efficient (Doomernik 2015). Therefore, efficiency is not enough to represent the performance in some cases, and the results can be comprehensive by combining the efficiency score with other factors. In this context, the performance matrix is adopted as a secondary step to present this decomposition graphically, which shows both efficiency and profit as an ellipse for each Decision-Making Unit (DMU). Furthermore, to provide a more complete recommendation, regression analysis is integrated as a third step in the model. This proposal aims to address how to improve the productivity and efficiency of the units in a chain, to develop a decision model that enables better decision making within the operation stage by learning best practices from efficient units, and to identify the reference set to improve the efficiency of inefficient units. Figure 1.2 summarizes the initial main parts of the research including the problem, motivation, and focus.

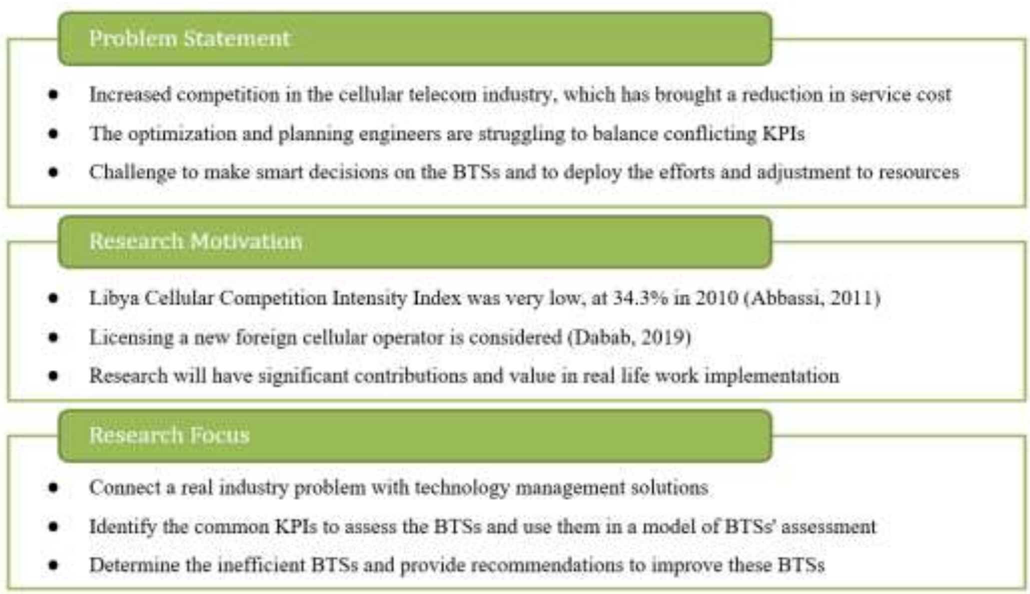


FIGURE 1.2: THE RESREACH PROBLEM, MOTIVATION, AND FOCUS

1.1 Problem Statement

Economists are expecting a complete renewal in the Libyan telecommunications market, including technology policy reform and regulation changes (Chavula 2013, Casey 2014). Furthermore, a study was conducted to assess the cellular providers in Libya for positional improvements, and the results show that licensing a new foreign operator is the best option for long-term investment in the Libyan cellular telecom industry (Dabab *et al.* 2019). Therefore, local mobile companies should be aware of and prepared for those changes. The Libyan mobile telecom sector has undergone a significant process of transformation because of the significant government policy reforms after 2011 despite the lack of competition in the past. This has led to an increase in the number of mobile providers, which has brought competition and a reduction in the service cost. Measuring the efficiency of the service and mobile infrastructure are increasingly important, and firms can sustain their competitive advantage by maintaining superior resources that are efficient. However, the optimization and planning engineers are struggling to balance conflicting KPIs, assess the importance of the BTS, and know which BTSs do not provide the best practices. As a result, the challenge is to make smart decisions on the BTSs, and to deploy the efforts and adjustments to resources that enhance the quality of service. Finally, there is a lack of a comprehensive decision model to enable better decision making within the mobile telecom infrastructure.

1.2 Research Motivation

The son of Libya's president controlled the telecommunications sector for a long time, and all of the decisions were made under his policies. As a result, the

Libya Cellular Competition Intensity Index was low at 34.3% in 2010 (Abbassi 2011). However, after the policy reforms in 2011 and the Libyan mobile telecom sector transformation, many global providers consider the Libyan market once the country will be stable. This brings concerns for the local providers to keep their market with the new competitors. Therefore, the local providers should be efficient and work hard to achieve the competitive advantage. The critical point of maintaining customer satisfaction with cost-effective services is mastering resource management and obtaining an efficient system. Therefore, optimization and planning engineers spend many hours analyzing massive amounts of data to evaluate the BTSs using many KPIs to enhance mobile coverage. In my previous job, as a Network Optimization and Planning Engineer, my colleagues and I struggled to balance conflicting KPIs to make best practice decisions since each KPI tells a different story. There is not one single KPI that tells the whole story, so we need to think in multidimensional ways to evaluate mobile towers. This process needs visual imagination and an algorithm that compares thousands of mobile towers with multi-inputs, multi-outputs, and a ton of data. It is difficult to compare multiple BTSs with many KPIs to assess the BTS based on the efficiency to enhance the performance of inefficient BTSs. Given these elements, this research will have significant contributions and value for implementation.

1.3 Research Focus

The research will identify the common KPIs to assess the BTSs, and use them in a model of BTS assessment to determine the inefficient BTSs. It will also provide recommendations to improve these BTSs. To ensure the reliability and maturation of the model, I will validate the model and the results with the experts in this field. This research suggests several things the radio cellular network engineers can do to improve the network performance starting with evaluating the efficiency based on multiple KPIs, and ending with changing the BTS configuration and settings based on best practices.

The rest of the proposal is organized as follows. First, the report provides an overview of the literature related to the productivity and quality of service, including the telecom mobile industry efficiency measurement. This will highlight the gap analysis, in which I will show my research gaps, objectives, and goals. The next section includes an introduction of the methodology as well as the comparison with other decision-making methods and data mining techniques. Then, my research plan and expected model steps with the validation process are presented. The last section explains the significant and potential implications of the mobile telecom industry, as well as the limitations and potential improvements in the leading research.

Chapter 2 Literature

The literature is divided into three main steps, and each one has several areas that are considered. Figure 2.1 shows the overall literature review parts.

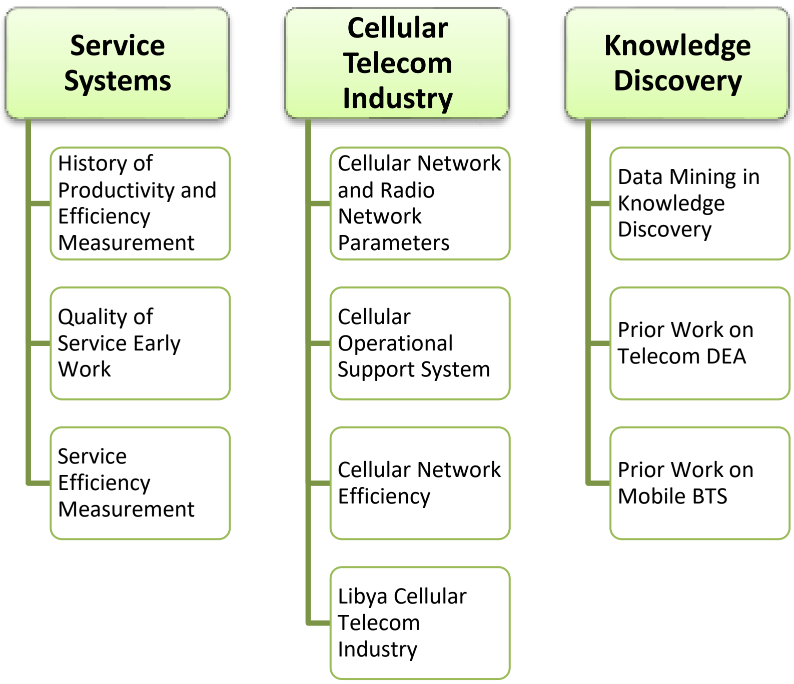


FIGURE 2.1: STRUCTURE OF THE LITERATURE REVIEW

2.1 Service System Science

There has been rapid growth in the service sectors, and service systems can be considered numerous (Maglio *et al.* 2009). Over the decades, science service has become the most substantial part of most industries, and it has attracted the attention of many researchers. Maglio and Spohrer defined the fundamentals of service science as a study of service systems that help to create a basis for systematic service innovation, and they found that the primary objective of this area is to improve the ability of efficiency, effectiveness, and sustainability of the service systems (Maglio and Spohrer 2008). Additionally, the essential focuses of science service are the theory of service systems, dynamic configurations of resources, and the connection between providers and customers (Lusch *et al.* 2008). With that, there are many challenges and opportunities for service science (Maglio *et al.* 2006, Maglio and Spohrer 2008). One of the significant points is managing service quality. The quality of the service in service science is connected to processes, people interactions, innovation, and productivity, and to the efficiency measurement of the business units. One study highlighted that due to the increasing importance of service systems, there has been a focus on the quality of technology measurements within consumer services (Akter *et al.* 2019). To conclude, it is apparent that efficiency and productivity are strongly linked in service systems.

2.2 History of Productivity and Efficiency Measurement

In economics and econometrics, the concept of total productivity was created from the Cobb–Douglas production function, which is a particular form of the production function. This concept was developed and tested against statistical evidence during 1927–1947, and it represents the technological relationship between capital and labor as inputs, and the amount of output that can be produced by those inputs (Cobb and Douglas 1928). The Cobb-Douglas production function form is considered a parametric approach, which has been widely used in practical applications to study the efficiency of resource allocation. However, this form had some restrictions that were clarified with the translog production function (Berndt and Christensen 1973).

The concepts of frontier production and efficiency measures began with the contribution of Debreu (Debreu 1951) while Koopmans (Koopmans 1951) defined technical efficiency as an input vector in producing an output vector. Another contributor used programming methods to understand the measurement of productivity efficiency to determine the input-per-unit-of output values (Farrell 1957). This concept defined the ratio, OB/OA, as the technical efficiency of the firm with input-per-unit-of-output values at some point. Based on this, the significant addition on the production function estimation was distributed between the work of (Aigner and Chu 1968, Afriat 1972, Richmond 1974), starting with the assumption that particular inputs give a maximum possible output. Aigner and Chu used a parametric approach to frontier production function estimation incorporating a specific functional form allowing for probabilistic distributions of inefficiency giving rise to stochastic frontier analysis (SFA). Afriat built on this approach by proposing that the path of the production function that holds the maximum possible output with a set of inputs also minimizes the input with some level of outputs. Afriat's purpose has some motivation to estimate productive efficiency when the production function is Cobb-Douglas for the empirical applications that underlay the distribution of the error term in the production.

A few years later, a proposal was defined for an alternative approach to the estimation of the frontier production function with a small difference with the efficiency measure of Richmond's (Meeusen and Den Broeck 1977). During the same year, another study utilized characteristics of various aspects of maximum-likelihood estimation for the coefficients of a production function with an additive disturbance term (Aigner *et al.* 1977). By utilizing the perspective of distinguishing between efficient and inefficient units, Färe described the technological assumptions with less restriction than those of Farrell for measuring the technical efficiency of production (Färe and Knox Lovell 1978).

2.2.1 Quality of Service Early Work

Maintaining a high quality of service is one of the critical factors to achieve customer satisfaction. Evaluating service quality has become an increasingly vital strategic role. Hanson and Kalyanam defined service quality as the ability of the organization to show and meet customers' needs and desires (Hanson and Kalyanam 2000). This definition works with most of the service providers. However, Johnston and Jones pointed out that the input/output relationship between operational productivity and customer satisfaction are not always positively or negatively related (Johnston and Jones 2004).

In the 1980s, there were several significant findings and attempts to frame the quality of services and understand consumer satisfaction. Many studies pointed out that one of the key strategic factors to differentiate the firms and to increase profits and market share in maintaining the service quality (Phillips *et al.* 1983, Buzzell and Gale 1987). Therefore, there has been a strong focus on how to manage the quality of services to maintain customer satisfaction by developing strategies to meet customer expectations (Parasuraman *et al.* 1988). In 1988, Zeithaml, Berry, and Parasuraman found four gaps in service quality, and discuss how it might be facilitated for the organizations (Zeithaml *et al.* 1988). Researchers focused on the process in which consumers evaluate service quality and complaint management (Hirschman 1970, Fornell and Wernerfelt 1987), and loyalty (Reichheld *et al.* 1996, Dowling and Uncles 1997).

Among consumer-motivated research, some studies focused on improving customer retention by developing a framework of accountable resources allocation (Rust and Zahorik 1993): building a model for antecedents of satisfaction (Anderson and Sullivan 1993), creating programs and scenarios on customer satisfaction (Anderson *et al.* 1994, Jones *et al.* 1995), understanding the difference between expected and perceived performance (Tse and Wilton 1988, Bolton and Drew 1991, Cronin and Taylor 1992), and measuring service quality, all have many elements of focus such as tangibles, reliability, responsiveness, assurance, and empathy (Parasuraman *et al.* 1985). However, dealing with perishable goods and intangible services adds challenges to measuring productivity in the service industry (McLaughlin and Coffey 1990). Additionally, from a financial perspective, researchers have examined and explained how service quality affects the firm's profit (Rust *et al.* 1995, Zeithaml *et al.* 1996).

Some researchers developed a formal model of the effects of complaint management as a tool of defensive marketing (Fornell and Wernerfelt 1987). Others advocated for customer retention as a more credible source of outstanding performance (Reichheld and Sasser 1990). The QoS should be evaluated and measured since most of the customers are looking for network performance and quality (Kumar *et al.* 2002, Seytnazarov 2010). Therefore, many firms have generated quality measurement programs that endeavor to connect services to quality evaluation (Hauser and Clausing 1988). There are several challenges in maintaining the QoS, each requiring a slightly different approach such as the complexity among inputs and outputs to operate the efficiency evaluation.

2.2.2 Service Efficiency Measurement

Drucker highlighted two main concepts: efficiency, which means doing things right, and effectiveness, which means doing the right things (Drucker 2012). Another simple definition of efficiency is the ratio of actual output to effective capacity (Johnston and Jones 2004, Slack *et al.* 2010). Over the past several years, there have been studies on how to solve the concern of delivering favorable services. Over the years, researchers also suggested that there is a strong connection between performance measures and increasing efficiency. In 2004, Johnston and Jones conducted an intensive investigation that focused on understanding the nature and components of service productivity, as well as the relationship between operational and customer satisfaction that provides a structure for improving the service efficiency in organizations (Johnston and Jones 2004). Some of the early studies linked the operational performance to a profit and cost ratio rather than the traditional efficiency measures, which are built on the cost-effectiveness of resources and revenue ratio. There are several ways to measure and evaluate performance such as the traditional ratio approach, regression rnalysis, multiple criteria analysis, analytic hierarchy process, balanced scorecard, delphi hierarchy process, total factor productivity, and DEA.

Additionally, in a study of the hospitality productivity assessment, Reynolds discussed three common productivity measures methods and highlighted the weaknesses with these methods. The first method was partial factor productivity measures that lacked comprehensive measures of operating efficiency, and the second was total factor productivity measures that were not able to provide comparative effectiveness for multiple operations. The last method was regression analysis that leads to generating benchmark information (Reynolds 2003). There are several challenges to maintain the QoS such as the complexity among inputs and outputs. This requires a slightly different approach to integrate multiple perspectives. Therefore, there needs to be a comprehensive tool and advanced performance model to enhance the performance of the services and assets. Also, choosing the right tool to build the model will help to make the model more acceptable to the managers.

The DEA method is commonly used to evaluate the efficiency of a group of producers which is referred to as Decision-Making Unit (DMU), and it allows the estimation of a production function that reveals the right input-output relations among a group of units. Use of DEA has been widely applied for measuring and benchmarking the relative efficiency in different applications. Furthermore, DEA has been used as a technique for the benchmarking of service performance for the providers and service operators. The introduction section refers to the DEA implication in the mobile telecom sector. Thus, some studies adopted DEA to analyze and evaluate the tourism and hospitality industry efficiency including tourism attraction (Wöber and Fesenmaier 2004, Barros *et al.* 2011), hotel and restaurant companies operating in India (Sanjeev 2007), and restaurants and hotels such as the efficiency of the restaurant sector across regions (Karakitsiou *et al.* 2018).

2.3 Mobile Telecom Industry

2.3.1 Cellular Operational Support System

The Operational Support System (OSS) provides and supports processes to maintain the network. The OSS is an overlooked component of the mobile network, but it plays an essential role to manage the network. Figure 2.2 illustrates the hierarchical architecture of the operation support system, which mainly is divided into:

- Performance management (PM)
- Fault management (FM)
- Configuration management (CM)
- User administration (UA)

Performance management helps check the performance of the network to generate plans for future use of the cellular network and to enhance the network's performance. Performance management includes:

- Quality of Service (QoS): A measurable set of parameters that define the level of service that a service provider can be accountable for.
- Service Level Agreement (SLA): Are the promises that firms are giving to their customers.
- Key performance indicators (KPIs): Indicate whether the individual network elements or services are forming overall QoS.

The KPIs are network parameters that are calculated based on the standard formula to indicate what is going on with the network. The user-formulas are based on the Statistics and Traffic Measurement Subsystem (STS) counters from object types in the BSC.

FIGURE 2.2: THE ARCHITECTURE OF OPERATION SUPPORT SYSTEM

2.3.2 Cellular Network Efficiency

Enhancing network performance and service quality is the most significant step for mobile providers to achieve customer satisfaction, which is directly related to profitability. Christan and Emmanuel pointed out that the key to sustaining a competitive advantage is connected strongly with customer satisfaction related to quality service delivery (Amadi and Essien 2016). Additionally, the quality of service becomes a priority in relation to the capacity of the network and the growing demand for the mobile services of the operators. There have been many studies that address the evaluation and improvement of the quality of service for a mobile communication system in developing countries (Popoola *et al.* 2009, Adegoke and Babalola 2011).

Thus, researchers have examined the performance implications of investments to improve the quality of services. They addressed the process of the customer satisfaction-loyalty link in which customers form expectations of service, perceive service performance, and then decide to continue with providers in the mobile phone service (Lee *et al.* 2001). Therefore, mastering resource management and obtaining an efficient system by analyzing the customer traffic behavior will help the mobile providers (Oladeji *et al.* 2013). In a comprehensive study to evaluate the performance of the mobile operating systems under varying traffic conditions, the author recommended developing management techniques to tune the technologies (Kyriazakos *et al.* 2002). Besides, in 2013, Oladeji, Onwuka, and Aibinu developed a forecasting model using the Artificial Neural Network method, which maps input to the output of service of BTSs to analyze the network traffic (Oladeji *et al.* 2013).

Research pointed out several methods to evaluate mobile network performance and measure the efficiency and productivity of mobile providers such as doing a survey, checking the coverage, and evaluating the interference, which are the indexes for measuring the quality of any mobile service (Kia *et al.* 1998). One of the conventional methods is the driving test, which shows the realistic experience of the customer—but it is difficult to perform every day for every network, and it costs a lot of money. Another evaluation method is using KPIs, which have been used to evaluate the performance of the operational networks in several studies, and which provide too many statistical details for each cell. However, those studies analyzed the efficiency of the network from each angle separately (Galadanci and Abdullahi 2018). Moreover, evaluating mobile network performance and measuring the efficiency bring challenges to the engineers since it needs multi-destination analysis to make the right decisions. While many studies highlighted that the assessment of quality service in the mobile providers builds on many dimensions using key performance indicators (Reliability, Responsiveness, and so on) (Parasuraman *et al.* 1985, 1988, Zeithaml *et al.* 1996, Amadi and Essien 2016, Osunade and Oyesanya 2016), there is not a comprehensive method that includes all these factors to come up with one single decision to improve efficiency.

A 2014 study that focused on evaluating the performance of GSM Networks concluded that providers should enhance the efficiency of the base station (Adekitan 2014). In terms of GSM operator performance, the study found that the low efficiency of the BTSs, which is the primary infrastructure part of the network, was one of the most significant performance challenges. In addition, another study recommended focusing on upgrading and optimizing the efficiency of the base station (Amadi and Essien 2016). Thus, in a study of the roles of the BTS on service delivery and maintaining customer satisfaction, the authors found that there is a need for an intelligent tool to enhance the BTSs (Alenoghena and Emagbetere 2012). The prior work on BTS efficiency mainly focused on power saving and the improvement of the energy efficiency of the BTS since it consumes over 80% of the network's power (Richter and Fehske 2009, Mclaughlin *et al.* 2011). We can divide the work into four areas, and Table 2.1 shows the conclusions of the BTS's research based on the themes:

- First, positioning the mobile base station to study the performance evaluation (Molina *et al.* 1999, Mollanejad *et al.* 2010, Abasikeleş-Turgut 2016, Tohma *et al.* 2016).
- Second, addressing the power consumption of mobile radio networks to reduce the environmental impact (Zhang *et al.* 2010, Hasan *et al.* 2011, Oh *et al.* 2011, Bianzino *et al.* 2012, Wu *et al.* 2015).
- Third, the evaluation of cellular mobile communication networks to increase the capacity and minimize the interference (Everitt and Manfield 1989, Karakayali *et al.* 2006).

- Fourth, focusing on electromagnetic radiation and BTS efficiency analysis to ensure human health and safety (Hutter *et al.* 2002, Moulder *et al.* 2005, Kim and Park 2010, Buckus *et al.* 2017, Singh and Gautam 2018).

TABLE 2.1: PRIOR BTS'S RESEARCH FOCUS SUMMARY

Themes	Description	References
BTS Location	The positioning of the Mobile Base Station to study the performance evaluation of BTS	(Molina *et al.* 1999, Mollanejad *et al.* 2010, Abasikeleş-Turgut 2016, Tohma *et al.* 2016)
BTS Power Consumption	Address the power consumption of mobile radio networks to reduce the environmental impact	(Zhang *et al.* 2010, Hasan *et al.* 2011, Oh *et al.* 2011, Bianzino *et al.* 2012, Wu *et al.* 2015)
BTS Capacity	Evolution of cellular mobile communication networks to increase the capacity and to minimize the interference	(Everitt and Manfield 1989, Karakayali *et al.* 2006)
BTS Radiation	Focus on electromagnetic radiation and BTS efficiency analysis to ensure human health and safety	(Hutter *et al.* 2002, Moulder *et al.* 2005, Kim and Park 2010, Buckus *et al.* 2017, Singh and Gautam 2018)

Thus, most of the studies have focused on comparing the companies either in the same country or in different countries from the financial perspective, and others from the customer satisfaction point of view. Table 2.2 summarizes the literature based on the perspectives. Furthermore, the majority of the studies in the mobile telecom sector focused on the financial side of the industry, such as revenue as an output, and assets, cost, and labor as inputs (Resende 2000, Cooper *et al.* 2001, Liao and Wang 2003, Zhu 2004, Liao and González 2009, Banker *et al.* 2010, Chen and Wang 2010, Cho and Park 2011, Liao and Lin 2011, Usero and Asimakopoulos 2013, Kwon 2014, Gökgöz and Güvercin 2017).

From the technical point of view, Rauer studied the workflow of the sites' maintenance to compute productivity for the providers' field force technicians (Rauer 2014). This study tried to measure the productivity of the engineers in a German mobile service provider based on three inputs and two outputs, but it is not clear how the author implemented DEA as well as the results. In another study, the authors focused on performance analysis of the utilities Indian mobile telecom sector. They measured the technical change and pure efficiency change taking into consideration parameters like network performance, billing complaints, and the number of subscribers (Nigam *et al.* 2012). A similar study was done on the mobile telecom industry of Mongolia to determine the changes in total factor productivity, but this study used different inputs and outputs and illustrated the effectiveness of competitive police of the market (Byambaakhuu *et al.* 2012).

There was also research done on the Malaysian mobile telecom industry to explore productivity growth, and the author found that there was great potential to further increase the industry's output (Mohamad 2004a, 2004b). Another study compared the 126 utilities of the Indian mobile telecommunication sector (Nigam *et al.* 2012). The authors had a difference of opinion around choosing the inputs and outputs. For instance, the number of subscribers should be in the input, and the number of successful calls should be in the outputs. However, the authors used a sensitivity analysis to select the strength of variables for performance improvement, which made this study interesting.

Finally, similar research to this study was done in 2010 where the authors identified the efficient and inefficient BTS to provide technical recommendations to increase the efficiency of the inefficient sites, which is practically senseless (Taghizadeh and Ebrahimi 2010). However, the model was built based on the site costs as inputs and traffic measurement as outputs, which is still not a technical efficiency point of view.

TABLE 2.2: TELECOMMUNICATION EFFICIENCY RESEARCH SUMMARY USING DEA

Themes	Description	References
Financial Perspective	Consider the revenue as output and assets, cost, and labor as inputs	(Resende 2000, Cooper *et al.* 2001, Liao and Wang 2003, Zhu 2004, Liao and González 2009, Banker *et al.* 2010, Chen and Wang 2010, Cho and Park 2011, Liao and Lin 2011, Usero and Asimakopoulos 2013, Kwon 2014, Gökgöz and Güvercin 2017)
Technology Perspective	A firm's technology that is being adopted, service quality overtime of the operators, and packages of prepaid mobile telephony with each price of the package	(Smirlis *et al.* 2004, Resende and Tupper 2009, Haridasan and Venkatesh 2011)
Productivity Perspective	Explore the productivity growth of the mobile telecom industry, productivity change of the leading mobile operators	(Mohamad 2004a, 2004b, Usero and Asimakopoulos 2013)
Technical Perspective	Measure the technical change and pure efficiency change, the traffic-measurement of the BTS, the workflow study of the sites' maintenance	(Taghizadeh and Ebrahimi 2010, Byambaakhuu *et al.* 2012, Nigam *et al.* 2012, Rauer 2014)

2.3.3 Cellular Network and Radio Network Parameters

Mobile radio coverage is divided into many hexagons with each one covered by a mobile Base Station (BS) (Mac Donald 1979). The significant part of the infrastructure-related costs results from the radio access network, so the strategy and best way to reach the desired results is by focusing on the BTS. While the rapid adoption of 3G, 4G, and soon to be 5G for mobile operators is established in most of the developed countries, the cellular operators in developing countries are still predominantly based on the 2G technology (GSM). For example, in Nigeria, more than 98% of cellular subscribers are using 2G technology (Ilyas *et al.* 2016). The second generation (2G) of mobile networks was deployed in the early 1990s and was designed based on Circuit Switching (CS) and Packet Switching (PS). In the 2G technology, the mobile phone call starts with a request channel, channel activation, channel allocation, and then the call initiates. With these processes, the counters in BSC measure the information, which then later will be turned into KPIs using standard formulas. Also, after the calls are connected, other counters count the abnormal call drop or failures (Kumar *et al.* 2002).

The research focuses on Radio Network Resources, which comprises of a Mobile Subscriber (MS) and Base Station (BS). Base Station System (BSS) Components are responsible for all the radio-related functions in the system, and management of all radio communication with the mobile station. The Base

Transceiver Station (BTS) is one of the main parts of the mobile network, and it controls the radio interface to the Mobile Station (MS). A Base Station Controller (BSC), which manages all the radio-related functions of a GSM network, controls a group of BTSs. BTS is a part of a cellular network that has multiple transceivers (TRX), and is known as a base station (BS), radio base station (RBS), or node B (eNB). The BTS facilitates wireless communication between the subscriber device "mobile phone" and mobile operator network. It handles the transmission and reception of signals, and the sending and reception of signals to or from higher network entities. Each BTS has one or more cells, but the most common number is three cells. One of the essential factors in determining the capacity of the cell is the number of TRansceiver Unit (TRU), which has eight physical channels, and time slots in one TDMA frame, which are used to transmit speech, data, or signaling information. Inside these channels, there are messages called logical channels. These are divided into control channels such as the Stand-alone Dedicated Control CHannel (SDCCH) and traffic channels, such as the Traffic CHannel (TCH).

2.3.4 Libyan Mobile Telecom Industry

With all the changes and challenges in the Libyan situation, the country possesses many positive attributes for carefully targeted investment in several sectors, and seeks to use the latest updated technology to improve public service (Khalifa *et al.* 2019). However, due to rapid and discontinuous changes in telecom technology, market demand, future-focused enterprises, and Libyan circumstances, the Libyan Ministry of Telecommunication needs to increase the organizational responsiveness of the telecom sector through the redesign and development of the existing companies, and the implementation of innovative strategies and processes. Therefore, there are many alternatives including adapting, integrating, and re-configuring for the cellular telecom infrastructures.

Libya has two local operators, Almadar Aljadid and Libyana Mobile Phone Companies, which are managed by Libyan Post Telecommunications and Information Technology Company (LPTIC) under the Libyan Ministry of telecommunication. The LPTIC was established in 2005 as a holding company to the owner of major communications companies in Libya ("LPTIC overview, website" n.d.). The purpose of creating LPTIC was to guide the investment in telecommunications infrastructure in the country and abroad in developing the new Libya telecom and information technology services-based economy, and in meeting customer satisfaction.

Almadar Aljadid was established in 1995 as the first mobile operator in Libya and North Africa, and it has over three million subscribers including government establishments, businesses, and individuals. It is well known for its high-quality services (Aljadid n.d.). On the other hand, Libyana started its first mobile services in September 2004 and quickly achieved success in the market with a high number of subscribers of more than 6.2 million subscribers during the first four years, which is about 116% of the Libyan population ("Libyana...The biggest mobile operator in Libya" n.d.). Thus, Libya recently tried the phenomenon of the Mobile Virtual Network Operator, where the two providers, Libyan and Almadar, leased their network and sold minutes of communication to the third-party providers. However, these third-party companies were under the same Libyan Ministry of Telecommunication that monitors telecom services, LTT, and Aljeal Aljadid, but they did not have networks. This experiment was not successful. Although the Ministry and its national operators have since sought to catch up with the fast growth of the technology and provide the best service to customers, the sector needs some reforms. As a result, the Libyan Ministry of Telecommunication is interested in long-term investment in the cellular telecom industry to enhance the mobile telecom sector. A study using the Hierarchical Decision Model (HDM) based on Libyan experts' judgments in the telecom sector found that licensing a new foreign operator is considered the best option in the case of Libya (Dabab *et al.* 2019). In doing so, the local providers should prepare for the coming situation.

2.4 Knowledge Discovery in Data Science

During the intervening decades, there was a significant improvement in innovations of computer systems and growth in databases, which led to introducing new technologies to use information and knowledge intelligently. The phrase "knowledge discovery in databases" was coined at the first knowledge discovery database workshop in 1989 to emphasize that knowledge is the end product of a data-driven discovery (Piatetsky-Shapiro 1990). It has been popularized in related research fields such as AI and machine learning, pattern recognition, databases, statistics, knowledge acquisition for expert systems, data visualization, and high-performance computing (Fayyad *et al.* 1996a). Kurgan and Musilek pointed out that the main driving factor in this workshop, which led to define the name, was the fact that knowledge is the end product of a data-driven discovery process as well as developing interactive systems that would provide visual and perceptual tools for data analysis (Kurgan and Musilek 2006).

Later, Piatetsky-Shapiro contributed to the research through an article on how the workshop introduced the Knowledge Discovery Database (KDD) in real databases with the use of the domain, and defined the future direction of the research in this area (Piatetsky-Shapiro 1990). KDD applications are emerging in many industries including retail, banking, telecommunication, manufacturing, and so on. The KDD process is usually generated using either two approaches, which domain experts manually analyze and judge according to their knowledge, or more statistical performance involving real-life data (Kurgan and Musilek 2006). In this research, I focus and care more about the second approach. The literature indicated that the term was extended to include other names such as knowledge extraction, information discovery, information harvesting, data archeology, and data pattern processing (Kurgan and Musilek 2006).

However, the meaning and the objective—comparing the terms—are still the same. Pattern discovery, which is the detection of signals in local structure data, is describing data with an anomalously high density compared with what would be expected in standard ways (Hand 2007). The first and well-known contribution books of the Knowledge Discovery Framework are "Knowledge Discovery in Databases" (Piateski and Frawley 1991) and "Advances in Knowledge Discovery and Data Mining" (Fayyad *et al.* 1996b). The knowledge discovery process includes many steps (Rogalewicz and Sika 2016). Data mining is used to refer to one of the steps for knowledge discovery in databases, and sometimes as a whole process of KDD (Cios and Kurgan 2005, Kurgan and Musilek 2006, Mariscal *et al.* 2010). Other schedulers considered it a core part of the KDD process or one of the critical steps of KDD (Cios and Kurgan 2005). In general, data mining is a systematic approach, which is referred to as knowledge discovery.

2.4.1 Data Envelopment Analysis (DEA)

The early work of Charnes and Cooper contributed to the translation of the linear-fractional program into the equivalent linear program by using the assumption that the feasible region is non-empty and bounded (Charnes and Cooper 1962). This conversion method solved the issue of convex function for the denominator and nonlinear properties, and the transformation technique used for the actual computation of the efficiency scores. The start of the DEA method was a new definition of efficiency, and a production function using modern methods of securing estimates of the economic concepts.

The DEA method is nonparametric and measures the efficiency of a series of DMUs using linear programming models (Charnes *et al.* 1978). The authors were initiated with a new definition of efficiency, and came with many ways of evaluating the efficiency of DMU's to enhance the planning and control activities in public programs (Charnes *et al.* 1979). The DEA method deals with multi-inputs and multi-outputs problems by using elements from the economic theory turned instead of linear programming. This made it possible to deal with the issues gracefully, which greatly expanded in the range of applications. Many authors have used and developed DEA for a great variety of practical problems, as well as for a variety of applications that have led to many extensions and further development in DEA. This research has led to new demand and developments.

2.4.1.1 Why Data Envelopment Analysis

We can see the advantages of DEA through the following points:

- The DEA objective can be maximized outputs or minimized inputs.
- DEA naturally handles multiple inputs and multiple outputs simultaneously and is robust with respect to multicollinearity among inputs and among outputs.

- Do not need to make strong assumptions such as for functional form of the relationship between inputs and outputs or of the statistical distribution of inefficiency.
- The efficiency scores for the DMUs are readily understandable and straightforward to convey to decision makers.

2.4.1.2 Advantages and Disadvantages of DEA

The DEA method has been used in various industries to measure the efficiency of DMUs. However, it is not always the right method to solve any problem, but it is appropriate in some instances where the issue meets the criteria of the strong points that the DEA has. In fact, many studies pointed out the advantages and disadvantages of DEA (Banker 1984, Bowlin *et al.* 1984, Andersen and Petersen 1993, Fare *et al.* 1994, Donthu and Yoo 1998, Seiford 1999, Ramanathan 2003, Aruldoss *et al.* 2013). This section highlights DEA's advantages and limitations as well as challenges in its application. Past studies have found DEA to have many advantages versus other competing techniques. These are drawn from a broad variety of applications and relative to a wide range of techniques but are briefly summarized as the following:

- Accommodates both controllable and uncontrollable factors
- capability of handling non-economic factors

- It is a compelling strategic decision tool that managers can use to evaluate and prioritize their units regarding efficiency assessments
- DEA does not assume any specific functional form relating inputs to outputs
- Handles multi-inputs and multi-outputs in the model by comparing the DMUs directly against peers from multi-perspectives
- Able to be applied to the multi-input and multi-output production context
- Capable to apply weight restrictions on the inputs and output
- DEA does not require an assumption of a functional form relating the inputs to the outputs
- Can be applied to non-profit organizations
- DEA produces an efficiency frontier that it is based on the best performers and is insensitive to the inclusion of additional inefficient performers.
- Computes a single index of productivity
- Although the calculations and the process of the DEA might be confusing and complex, the results and scores of efficiencies for the DMUs are straightforward and understandable for anyone

Although DEA has been developed, it still has some limitations that researchers need to resolve, such as:

- The outcomes of the DEA are sensitive to the selection of inputs and outputs
- Defining the right inputs and outputs is considered a real challenge for building a comprehensive model
- The efficiency results of the DEA express the efficiency of each DMUs compared to each other, and not with the ideal efficiency
- Absolute and perfect efficiency cannot be measured
- There are not statistics tests that can be applied to the results, or that can test the significance of the inputs or outputs that are included in the model
- DEA is sensitive to outliers, as these serve to form the optimal frontier
- The error and noise in data have significant impacts, and cause problems with inaccurate results
- While it can differentiate between efficient and inefficient DMUs, having a threshold of the ranking is not possible
- Some applications found that negative data and zeros can lead to some issues in the results

2.4.1.3 Prior Work on Telecommunication Using DEA

Around forty authors have contributed to the implementation and development of the DEA method in the telecommunication industry. From the literature review, it is clear that there is limited research on implementing DEA in the telecom industry, and Figure 2.3 shows the most publications in this area since 1993.

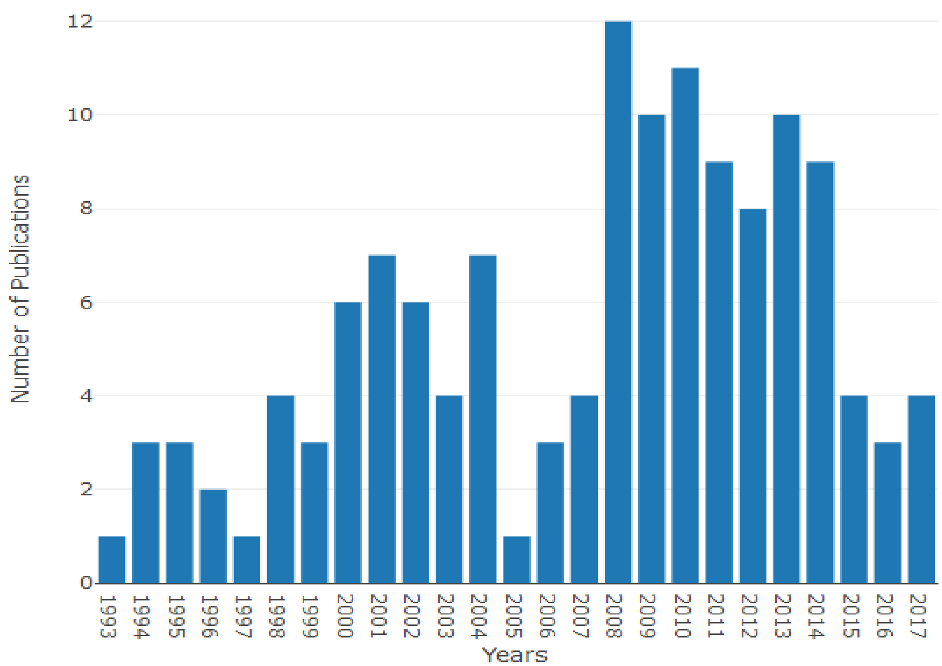


FIGURE 2.3: THE DISTRIBUTION OF THE DEA PUBLICATION IN THE TELECOMMUNICATION INDUSTRY

2.4.1.4 Prior Work on Cellular Efficiency Using DEA

In addition to the studies that have been carried out to evaluate the efficiency of the telecommunications industry, some studies have been conducted on the mobile telecom sector. The majority of the studies in the mobile telecom sector have focused on the financial perspective, which considers revenue as an output, and the assets, cost, and labors as inputs. However, the remainder of the papers have focused on various topics related to the mobile telecom aspect. Figure 2.4 shows the topic distribution of the papers. Additionally, Table 2.3 summarizes the in-depth literature, and lists the inputs and outputs for each article.

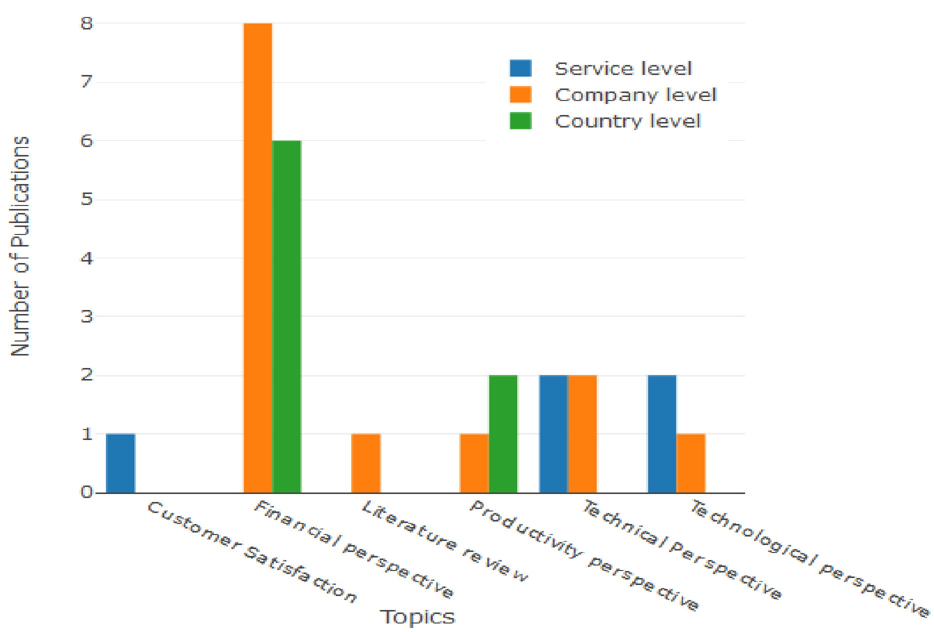


FIGURE 2.4: THE DISTRIBUTION OF THE LITERATURE PAPERS AMONG VARIOUS SOURCES

TABLE 2.3: SUMMARY OF THE LITERATURE FOR MOBILE TELECOM EFFICIENCY USING DEA

NO.	Authors 1	Title	Year	Journal	Country	Inputs	Outputs
1	Fazil Gokgoz, Mustafa Taylan Guvercin	Performance Benchmark of the Top Telecom Operators in the Mobile Era	2017	Recent Applications of Data	Turkey	1. Total assets 2. Capital expenditure 3. Total equity 4. Number of employees	1. Revenue
2	He-Boong Kwon, Paul Hong	Comparative efficiency assessment and strategic benchmarking of smartphone providers with data envelopment analysis	2015	International Journal of Productivity and Quality Management	USA	**Total asset model:** 1. current assets 2. property and equipment 3. other assets **Current asset model:** 1. Cash and cash equivalents 2. accounts receivable 3. inventories 4. other current assets **Expense Model:** 1. cost of sales 2. R&D 3. SG&A 4. depreciation and amortization	1. Sales
3	Hans Peter Rauer	Measuring Service Productivity: The Case of a German Mobile Service Provider	2014	Hawaii International Conference on System Sciences	Germany	1. time-on-site 2. traveling time 3. contract time	1. base stations served 2. urgency rating

4	He-Boong Kwon	Performance modeling of mobile phone providers: a DEA-ANN combined approach	2013	Benchmarking: An International Journal	USA	1. cost of goods sold (OGS) 2. research and development expenses (R&D) 3. sales, general and administrative expenses (SG&A)	1. sales revenue 2. operating income
5	Belen Usero, Grigorios Asimakopoulos	Productivity change and its determinants among leading mobile operators in Europe	2013	Appl. Econ.	Spain	1. Revenues of the mobile operator 2. The average revenue per user of mobile services	1. Total minutes of use of mobile services of mobile operator 2. Total number of subscribers of mobile services of mobile operator 3. Percentage penetration of mobile operator
6	Belen Usero, Grigorios Asimakopoulos	Benchmarking Mobile Operators Using DEA: An Application to the European Mobile Markets	2013	Book	Spain	1. total number of subscribers 2. total number of subscribers as a percentage captured by the mobile operator	1. Revenues 2. Average revenues per user of mobile services
7	Vineeta Nigam, Tripta Thakur, V. K. Sethi, R. P. Singh	Performance Evaluation of Indian Mobile Telecom Operators based on Data Envelopment Analysis	2012	J. Inst. Eng. India Ser. B	India	1. Call Success rate 2. call drop rate 3. voice quality	1. service access delays 2. complains 3. period of all refunds 4. number of subscribers

8	Erkan Bayraktar, Ekrem Tatoglu, Ali Turkyilmaz, Dursun Delen, Selim Zaim	Measuring the efficiency of customer satisfaction and loyalty for mobile phone brands with DEA	2012	Expert Syst. Appl.	Turkey	1. image 2. expectation 3. perceived quality 4. perceived value	1. customer satisfaction 2. customer loyalty
9	Badamasuren Byambaakhuu, Youngsun Kwon, Jaejeung Rho	Productivity growth and efficiency changes in the Mongolian mobile communications industry	2012	ITS Biennial Conference	South Korea	1. number of employees 2. amount of annual investment	1. call to own network, 2. call to other networks 3. call termination.
10	Vineeta Nigam, Tripta Thakur, V. K. Sethi, R. P. Singh	Benchmarking of Indian mobile telecom operators using DEA with sensitivity analysis	2012	Benchmarking: An International Journal	India	1. Expenditure in crores 2. Call success rate 3. Call drop rate 4. Voice quality	1. Service access delay 2. Complaints 3. No. of subscribers 4. Gross revenue in crores
11	Eun Jin Cho, Myeong Cheol Park	Evaluating the Efficiency of Mobile Content Companies Using Data Envelopment Analysis and Principal Component Analysis	2011	Electronics and Telecommunications Research Institute	Korea	1. total amount of assets 2. operating costs 3. employees 4. years in business	1. revenue

12	Chun-Hsiung Liaoa, Hsing-Yung Linb	Measuring operational efficiency of mobile operators in Japan and Korea	2011	Japan World Econ.	Taiwan	1. Number of employees 2. Total assets 3. Capital expenditures	1. Voice revenue 2. Data revenue
13	Vani Haridasan, Shanthi Venkatesh	CRM Implementation in Indian Telecom Industry – Evaluating the Effectiveness of Mobile Service Providers Using Data Envelopment Analysis	2011	International Journal of Business	India	1. Reliability 2. Responsiveness 3. Empathy 4. Assurance 5. Network Quality 6. Advocacy	1. Advocacy Loyalty Index 2. Purchase Loyalty Index
14	Houshang Taghizadeh, Mohamad Mehdi Ebrahimi	Evaluating the Efficiency of BTS sites of Mobile Telecommunication Company by Using DEA Method	2010	International Conference on Engineering System Management and Applications	Iran	1. Space 2.BTS site construction cost 3. System feeding cost 4. BTS site specified equipment cost 5. BTS site research cost 6. Transport equipment cost	1. Successful calls 2. Unanswered calls 3. Unsuccessful calls 4. Total calling time 5. Subscribers covered 6. The number of Successful handovers 7. Number of sent and received short messages
15	Rajiv D Banker, Zhanwei Cao, Nirup Menon, Ram Natarajan	Technological progress and productivity growth in the U.S. mobile telecommunications industry	2010	Ann. Oper. Res.	USA	1.cost of service 2. cost of equipment 3. selling 4. general and administrative (SG&A)	1. Equipment revenue 2. service revenue

16	Chun-Mei Chen, Tsung-Cheng Wang	Rising productivity of the fixed-mobile convergence trend in the telecommunications industry	2010	African Journal of Business Management	Taiwan	1. total assets 2. debts 3. SG & A expenditures	1. revenue 2. EBITDA 3. EBIT 4. net income
17	Chun-HsiungLiao, DianaB.Gonzále	Comparing Operational Efficiency of Mobile Operators in Brazil, Russia, India, and Chin	2009	China World Econ.	Taiwan	1. Number of employees 2. total assets 3. capital expenditure	1. Total revenue
18	Marcelo Resende, Henrique César Tupper	Service quality in Brazilian mobile telephony: an efficiency frontier analysis	2009	Applied Economics	Brazil	1. complaints rate 2. the coverage/congestion 3. the complaints 4. call interruption	1. contacts handled within 5 days 2. customers serviced in 10 minutes 3. completed calls 4. call establishment
19	Vineeta Nigam, Tripta Thakur, R. P. Singh	Evaluating the Performance of Mobile Telecom Operators in India	2009	International Journal of Simulation Systems, Science & Technology	India		
20	Joe Zhu	Imprecise DEA via Standard Linear DEA Models with a Revisit to a Korean Mobile	2004	Operation Research	USA	1. Manpower 2. operating 3. management	1. revenue 2. facility success 3. output (bounded)

		Telecommunication Company					
21	Noorihsan Mohamad	Regulatory Reforms and Productivity Performance of the Malaysian Mobile Telecommunications Industry	2004	book	Malaysia	1. total number of labors 2. fixed capital stock of lands and buildings 3. total number of mobile switching centers MSC 4. total number of radio base station RBS	1. Number of subscribers
22	Y. G. Smirlis, D. K. Despotis, J. Jablonsky, P. Fiala	Identifying "best-buys" in the market of prepaid mobile telephony: An application of imprecise DEA	2004	International Journal of Information Technology and Decision Making	Greece	1. Price	1. Startup Airtime 2. Service provider 3. Handset
23	Noorihsan Mohamad	Productivity growth in the Malaysian mobile telecommunications industry	2004	International Journal of Economics	Malaysia	1. total number of labors 2. fixed capital stock of lands and buildings, 3. total number of mobile switching centers (MSC) 4. radio base stations (RBS)	1. the number of subscribers
24	Chun-Hsiung Liao, Shaw-Er Wang	Comparing the Operational Performances of Taiwan Private Mobile	2003	knowledge economy and electronic commerce	Taiwan	1. number of employees 2. cost of telecom. services 3. number of base stations 4. promotion expense.	1. revenue

		Telecommunications Operators					
25	William W. Cooper, Kyung Sam Park, Gang Yu	An Illustrative Application of Idea (Imprecise Data Envelopment Analysis) to a Korean Mobile Telecommunication Company	2001	Operation Research	USA	1. Manpower 2. Operating cost 3. Level of management for facilities and customer	1. Revenue 2. Rate of facility failures 3. Rate of call completion
26	Marcelo Resende	Regulatory regimes and efficiency in US local telephony	2000	Oxford Economic Papers	Brazil	1. total number of employees 2. total number of access lines 3. total number of central office switches	1. local-service revenues 2. long-distance revenues 3. total-access and other revenues

2.4.2 Data Mining

Due to the complexity of data and problems, Frawley, Piatetsky-Shapiro, and Matheus found that there was a need to use more domain knowledge, efficient algorithms, interactive approaches, incremental methods, and integration levels (Frawley *et al.* 1992). The emergence of the standard Knowledge Discovery and Data Mining (KDDM) model was introduced several years ago (Kurgan and Musilek 2006), and over the past few years, there have been developments of the standard KDDM starting from first reported KDDM model by Fayyad *et al.* in the mid-1990s (Fayyad *et al.* 1996a), Cabena et al (Cabena *et al.* 1998), and several other models. These models helped to evaluate industrial applications in a variety of research and industrial domains (Cios and Kurgan 2005).

Moreover, Cios and Kurgan emphasized the importance of designing and integrating KDDM to help businesses respond more quickly and effectively to market demands, and to enhance operational efficiencies (Cios and Kurgan 2005). Data Mining, DM, is considered an essential way of discovering knowledge, and it has a significant role in decision-making. It is a beneficial tool for decision making, and it has been demonstrated in various industries. The general studies trends did not support KD activities, but they concentrated on the expansion of new and improved DM techniques and approaches (Kurgan and Musilek 2006). Through an

IBM project, researchers presented their perspective on database mining to emphasize a confluence of the performance database. They also highlighted three main algorithm classifications, associations, and sequences to cover the rule discovery framework (Agrawal *et al.* 1993a). Data mining methodologies have been developed, including Knowledge Discovery in Databases, Cross-Industry Standard Process (CRISP-DM), SEMMA, Human-Centered Approach, 5 A's, 6 Sigma, Cabena, Two Crows, Anand & Buchner, and Data mining for Industrial Engineering (Chen *et al.* 2015). At the time, these methodologies and process models were developed with different degrees of success, and no one technique could solve all problems. In fact, there are some limitations and challenges with each method, but every method has outstanding advantages. Due to rapid changes and developments as well as the vast number of methods, it is hard to describe the state of the art and the status of Data Mining and Knowledge Discovery models. Data mining has been developed to cover industry needs, as there is a variety of data and information available in different industries and real-world applications.

Data mining is a managerial tool used to answer future and current business questions using past data. The term data mining had negative connotations in statistics during the 1960s when computer-based data analysis techniques were first highlighted (Fayyad *et al.* 1996b). One of the initial definitions of data mining was that it is an extraordinary process or a mechanism of obtaining knowledge that is novel, useful, implicit, and comprehensive knowledge discovery from a massive of amount of data (Fayyad *et al.* 1996b, Rogalewicz and Sika 2016, Hussain 2017). Data mining is a learning model that analyzes data and recognizes patterns based on statistical learning theory. It produces a binary classifier, and it is widely used in text classification, marketing, and pattern recognition (Chen *et al.* 2015).

Throughout the literature, scholars defined data mining using different terms and a variety of names including acquiring knowledge, discovering knowledge, generating a lot of patterns, extracting interesting hidden patterns, extracting of information, knowledge extraction, discovering novel, information discovery, information harvesting, data archaeology, data pattern processing, data archaeology, and data dredging (Fayyad *et al.* 1996b, Chen *et al.* 2015). Data mining techniques were adopted originally from several fields of research including statistics, database systems, machine learning, expert systems, neural networks, intelligent databases, knowledge acquisition, and visualization. (Piatetsky-Shapiro 1990, Frawley *et al.* 1992, Agrawal *et al.* 1993a, Chen *et al.* 1996, Fu 1997). Since then, there are many areas that data mining is applied to such as retail, city governance, and insurance companies, medical and healthcare, education, financial and banking, cloud computing, telecommunications, transportation, agriculture, and engineering. Also, data mining application and functionalities can be used in e-commerce (Sarwar *et al.* 2000), industry, healthcare, and valuable business information. It can be applied to various problems in banking areas (Chitra and Subashini 2013, Pulakkazhy and Balan 2013), market basket analysis, and direct marketing (Ling and Li 1998).

In the 1990s, data mining including theory and algorithms applications were at the peak of the revolution of development (Cios and Kurgan 2005). Rogalewicz and Sika pointed out the main reasons behind increasing data mining usage into increasing data size were the inability of humans to process the extensive data, the ability to obtain more insights, and a wide range of problems (Toloo *et al.* 2009, Rogalewicz and Sika 2016). The drivers behind data mining were divided into several different areas: scientific and commercial (Hand 2007); identifying exciting patterns; extracting hidden information; making customer relationship management possible; gaining a competitive advantage; characterizing customer activities; learning behavior, skills, and emotions; improving security; and protecting BI and customer privacy (Qiu *et al.* 2008, Deepashri. and Kamath 2017). Data mining approaches and processes are built based on several fields including machine learning, statistics, pattern recognition, artificial intelligence, database systems, and mathematical statistics. As a rule, they are used for soft modeling, as opposed to solid modeling where models are based on differential equations from mathematical physics. These approaches are used to model unknown phenomena with a high level of complexity (Rogalewicz and Sika 2016).

2.4.2.1 Data Mining Process

Data mining is known as the extraction of useful information from different vast data sources through several steps to get the results. The results of these sequence steps will help in making decisions and answering questions to forecast future trends. Several methodologies have evolved over the previous years, and the data mining process is subjected to the methodology used by analysts. However, most of the researchers present data mining in almost the same steps and processes (Bharati 2010, Chen *et al.* 2015). In general, data mining has three main steps to process and define the problem, which breaks down to exploring, building models, exploring and validating models, deploying and updating models. Figure 2.5 illustrates the steps in more detail, and the main objectives of the primary three levels are:

- Data preparation for mining including data cleaning, data integration, data selection, and data transformation.
- Identification of the patterns that find the patterns, and that evaluate patterns of discovered knowledge.
- Data deployment that presents and visualizes the data to the user.

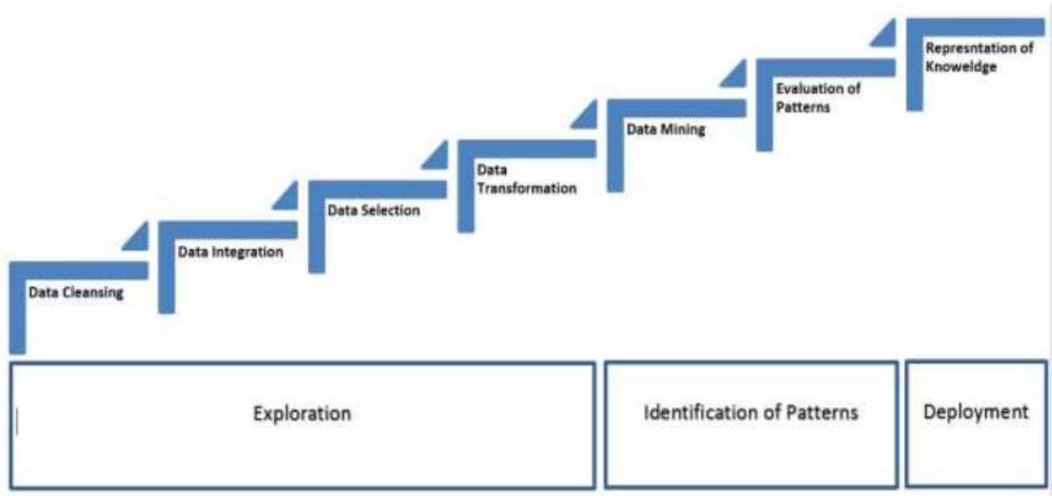


FIGURE 2.5: DATA MINING PROCESS USE ADOPTED FROM (DEEPASHRI. AND KAMATH 2017)

Data mining is known as the extraction of useful information from different vast data sources. However, there is no single algorithm or technique that works best across all types of datasets and problems. Data mining has many techniques that have proven very useful in many domains. However, no single algorithm or technique works best across all types of datasets and problems.

2.4.2.2 Data Mining Approaches and Techniques

Several approaches and methods are categorized as data mining, and the literature indicated many algorithms such as gap statistic algorithms, chi-square automated interaction detection, models and algorithms, GRASP, OLAP, clustering algorithms, decision forest algorithms, genetic algorithms, Apriori algorithms, Euclidean distance, bagged clustering algorithms, fuzzy logic, anomaly-based IDS, clustering, and CRISP-DM models. However, recently, researchers have come up with the top ten data mining algorithms that cover different data mining techniques. They include C4.5, k-Means, SVM, Apriori, EM, PageRank, AdaBoost, kNN, Naïve Bayes, and CART (Wu *et al.* 2008, Li 2015).

Several data mining techniques were developed, which were driven by the top 10 algorithms mentioned above. Depending on the nature of the data mining technique, its functionality, and the objective of disciplines contributing to data mining, the methods are categorized, and researchers provide a classification of systems that may help users. For instance, one author classified the data mining tasks into summarization, classification, clustering, association, and trend analysis (Fu 1997), yet others inventoried the data mining tasks and goals under the following categories: data processing, prediction, regression, classification, clustering, association, visualization, and exploratory data analysis (Goebel and Gruenwald 1999). Some tend to explain the different data mining techniques based on the primary purpose of using data mining techniques either as a predictive model including classification, regression, time series analysis, and prediction, or as a descriptive model including clustering, summarization, association rules, sequence discovery (Chen *et al.* 1996, Hussain 2017). In this research, we can divide the data mining techniques according to the techniques' objectives; those closest together and most related form five groups: classification, clustering, predicting, association, and combination modeling. Figure 2.6 illustrates the critical DMT trends and an example of each category. The examples of classification I gave are based on the more well-known methods and the similarity with the original research.

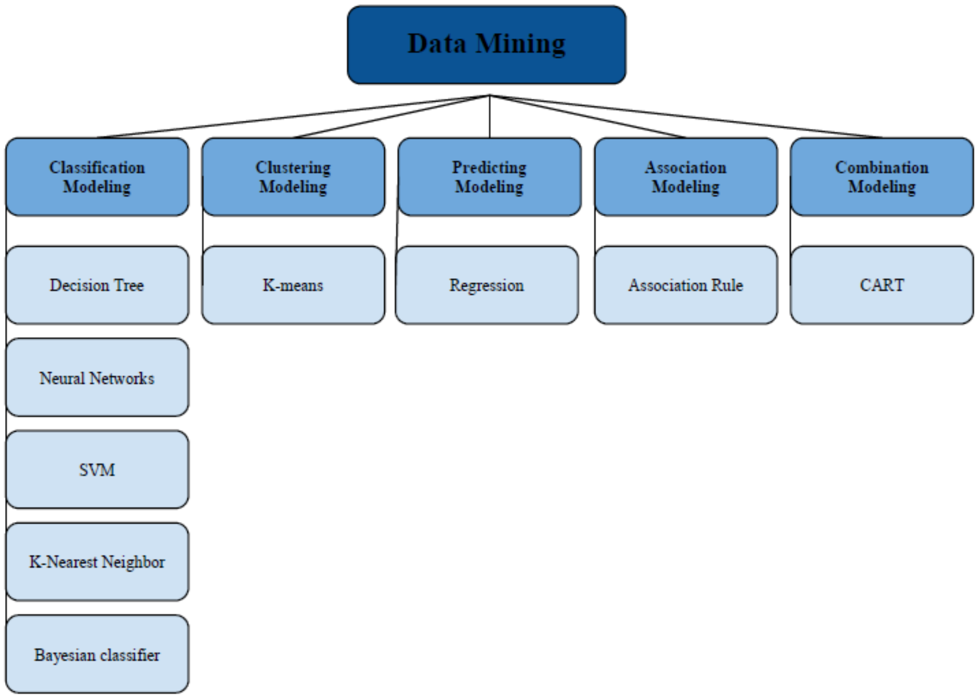


FIGURE 2.6: DATA MINING TECHNIQUES CATEGORY

2.4.2.2.1 Classifications Modeling

Classification techniques can be used in conditioning and monitoring, and pattern recognition in control charts, which involves learning and classification using a training data to learn and build a classification algorithm that is used to estimate the accuracy of the classification rules in test data. Phyu highlighted in his comprehensive survey that classification methods are reliable in modeling interactions (Phyu 2009). There are several kinds of classification methods that are available in the literature, but I focus on the widely used approaches.

- **Decision Tree**: This is a method that classifies instances by sorting them based on a feature of values, and it is usually unvaried because there is a single function at each internal node. The decision tree is considered one of the most popular data mining and presentation techniques (Carneiro *et al.* 2017). Decision Trees can be interpreted as a hierarchical organization of rules. Decision Tree provides predictive analytic based on specific rules, and it is a graphical representation of relationships among variables in a tree-like format. In other words, it is a multi-criteria decision tool that leads to alternatives for each branch starting with a root node, and follows down until reaching a terminal node, and each terminal node represents a decision. Because of the replication problem, this method can be a substantially more complex representation for some thoughts (Phyu 2009). Additionally, a decision tree is easy to interpret and understand, but it generates too many rules to get reliable results (Dabab *et al.* 2018). For example, in bankruptcy prediction, the decision tree was found to be more accurate compared to neural networks and support vector machines, but one limitation of decision trees is that it generates too many rules (Olson *et al.* 2012). In conclusion, the decision tree is commonly used in data mining with the objective of creating a model that predicts the value of a dependent variable based on the values of several independent variables.

- **Neural Networks (NN):** This consists of a bunch of nodes each of which has a weighted connection to other nodes, and it is comprised of three stages of training, testing, and deployment. The neural network is one of the data mining techniques used for an accurate and reliable result. The method connects to input and output units, and it can extract patterns and detect trends that are complex. The efficiency can be measured using the neural network in two ways either by taking the ratio between the observed and predicted values for the inputs and outputs or by taking the more extreme transformation (Athanassopoulos and Curram 1996). One of the main advantages of neural networks over other data mining techniques is the ability to learn from the past, and to improve results as time passes, in other words, extracting rules and predict future actions based on the current situation (Ogwueleka 2011). In summary, it helps to recognize similar patterns, and predicts future information based on the associative memory of past data and patterns.

- **Support Vector Machines (SVM):** This consists of supervised learning techniques that are used for classification and regression, and it is mostly used in classification problems. The SVM classification separates the target classes, and on the other hand, the SVM regression builds a continuous function with data points (Chitra and Subashini 2013). The objective of SVM is to find the best classification function to distinguish between factors of the two classes in the data (Wu *et al.* 2008). Additionally, Agrawal and Agrawal reported that SVM has better accuracy when compared with neural-network techniques (Agrawal and Agrawal 2015). SVM is insensitive to the number of dimensions and requires only a few examples of training (Wu *et al.* 2008). In general, it is a simpler, faster, and less tuning-intensive method and is considered one of the most robust and accurate algorithms.

- **K-Nearest Neighbor (KNN):** This is particularly well suited for multi-modal classes and problems where the object can have many class labels since it is easy to understand and implement a classification technique. The method has three key elements: a set of labeled objects, a distance or similarity metric to compute the distance between objects, and the value of *k* (Wu *et al.* 2008). When new unlabeled data comes in, KNN uses distance metrics to compare with k-nearest neighbors in the training dataset and then makes the decision to classify it (Li 2015). Furthermore, the k-nearest neighbor algorithm takes its entire training data into memory to perform classification (Wu *et al.* 2008). However, the method has several drawbacks and issues including test records being unclassified, difficulty with choosing the value of *k* combining the class labels, problems choosing the distance measure, and

KNN classifiers being lazy learners (Wu *et al.* 2008). In another study, two issues were pointed out regarding the selection of *k* in KNN; first, if *k* a value of *k* is too small it *k* can make the model overly sensitive to noise, and second, a too-large value of *k* might include too many points from other classes (Wu *et al.* 2008). In conclusion, it is one of the simplest classification methods, and it is used in a variety of applications such as economic forecasting, data compression, and genetics.

- **Bayesian Networks (BN):** This is an unsupervised learning technique in which the learner does not distinguish between the class variable and the attribute variables. It is also known as a Naive Bayes classifier. The method is a directed acyclic graph that converts a joint probability distribution over a set of random variables and is known as a graphical model for probability relationships among a set of variables and structural relationships among them. The advantages of this method include calculating the explicit probabilities for the hypothesis and the ability to handle noise in input data (Phyu 2009). Moreover, a study on this pointed out that the Bayesian classifier is essential for various reasons including it is effortless to construct, easy to interpret, and often does surprisingly well. Moore and Zuev reported that Bayesian methods had been shown to work better than more complex methods, and they emphasized that the advantages of simplicity of this method ensure tractable process (Moore and Zuev 2005). The most noticeable feature of BN is the ability to consider prior information about a given problem. However, it is not suitable for datasets with many features (Phyu 2009). Thus, it is ignoring interactions between attributes within individuals of the same class, and Bayesian classifier using assumption often abbreviated to Naive Bayes. In summary, the Bayesian classifier is a simple probabilistic method based on applying Bayes' theorem with strong independence assumptions (Naïve), and it provides prior knowledge and a useful perspective for understanding.

2.4.2.2.2 Clustering Modeling

Clustering modeling identifies similar classes of objects and discovers the overall distribution pattern and correlations of attributes. Clustering is a statistical classification approach for finding out whether the individuals fall into different groups by making quantitative comparisons of multiple characters (Jain 2010). Clustering Techniques can be used in product defects, fault classification, product quality prediction, product design, and process anomaly detection. Berkhin explained that clustering could be defined as corresponding to hidden patterns from a machine learning point of view or an outstanding role in data mining applications from a practical aspect (Berkhin 2006). In general, the clustering approach can be divided into two categories: hierarchical clustering, which recursively finds nested clusters either in top-down mode or an agglomerative mode, and partitioned clustering that finds all the groups simultaneously as a partition of the data. The literature shows many techniques under clustering, and I cover the most popular of partitioned clustering.

- **Partitioning Methods (k-means):** The k-means is a popular clustering technique for data mining (Likas *et al.* 2003, Jain 2010). The technique was developed in the 1970s, and it is the most popular clustering tool by far (Berkhin 2006). It is a simple iterative method to partition a given dataset into a user-specified number of clusters; it has been discovered by several researchers across different disciplines, most notably (Lloyd 1957, Forgey 1965), Friedman and Rubin (Friedman and Rubin 1967), and McQueen (McQueen 1967). Also, it is the simplest method used to return a real-valued prediction for a given unknown sample, and it is based on learning by analogy. The k-means generates some groups from a given dataset to put the identical values or transactions under some predefined clusters, k. The user can define some clusters, and k-means return results accordingly. The k-means algorithm suffers from several limitations including sensitivity to initialization, limiting the case of fitting data by a mixture of *k* Gaussians with identical, isotropic covariance matrices, and responsive to the presence of outliers (Wu *et al.* 2008). Moreover, the disadvantages of k-mean clustering are that the lists in the initial grouping will determine the cluster significantly with small data, human determination of k, will unclear the real cluster using the same data, and will make an assumption that each attribute has the same weight (Lemos *et al.* 2005) as well as the point that Phyu mentioned—one of the drawbacks of this method which is known as lazy learner (Phyu 2009). However, k-means is used widely in the practice of the partitioned clustering algorithm. Moreover, it has some advantages including simplicity, being reasonably scalable, and easy to modify for streaming data (Wu *et al.* 2008). Likas *et al.* apply the global k-means algorithm to solve the data-partitioning problem (Likas *et al.* 2003). In general, the k-means under the clustering algorithm is suggested as one of the techniques for anomaly detection, which can do intrusion detection without prior knowledge (Agrawal and Agrawal 2015). The k-means technique is the most popular and simplest partitioning method, and it looks to minimize the sum of the squared errors over all *k* clusters.

2.4.2.3 Prediction Modeling

This is a tool used in predictive analytics, a data mining method that finds the relationship between one or more variables and forecasts future values. It is a statistical analysis process that evaluates the past and current data at hand to calculate the probability of specific results and predict a future outcome or behavior. Predictive modeling is the process of using known results to create and validate a model that can be used to forecast future outcomes. Regardless of the methods used, the main steps of the predictive modeling process are the same across methods, and includes creating a predictive model, using the model to forecast the outcome, and then validating a model (Kuhn and Johnson 2013). The most widely used predictive modeling technique is regression, which refers to a relationship between the input(s) and output variables.

- **Regression:** Regression analysis is one of the quantitative models that is used for decision-making by measuring the relationships between the independent and the dependent variables, and it has been used in many areas such as quality prediction, manufacturing process control, and process optimization (Rogalewicz and Sika 2016). It is a set of statistical steps that estimates the relationships among the dependent variable and one or more independent variables. Regression analysis encompasses many variations and is among the most widely used of all statistical techniques. While linear and logistic regressions are popular in many settings including predictive modeling, there are many other types of regression analysis such as nonlinear regression, multiple linear regression, stepwise regression, and ridge regression. Regression analysis is a valuable tool for modeling and analyzing data, and many books explain the method in more detail such as (Rencher 2003, Johnson and Wichern 2004, Weisberg 2005, Izenman 2008, Ritz and Streibig 2008, Chatterjee and Hadi 2015). Regression analysis can empirically test the results using R^2, which is often called the coefficient of determination. A higher R^2 suggests a useful model, and that reasonable inputs and outputs are in the model. Another trait of regression is the ability to determine the relative influence of the predictors to the outcomes with the *p*-value, wherein each independent variable tests the null hypothesis that the variable does not correlate with the dependent variable; a lower *p*-value is likely to be a statistically meaningful addition to the model. Regression models can estimate the model's success, and regression diagnostics help suggest improvements such as the residual plot indicating adding a higher-order term. While linear regression may have many limitations, many of these can be mitigated by applying a different type of regression analysis. The regression technique is usually used to estimate the effect on the average of resource variables with the probability of having a dependent variable (Lemon *et al.* 2003).

2.4.2.4 Association Modeling

Association modeling between sets of items was first addressed in a study (Agrawal *et al.* 1993b) to find regularities in the shopping behavior of customers and then has been applied to many application domains such as business analysis, telecommunications, bioinformatics, and web mining. Understanding customer behavior can improve sales and profits. A seller could understand the performance of his own business and may also identify customers' needs

(Deepashri and Kamath 2017). Association techniques can be used in total preventive maintenance, fault diagnosis, failure in manufacturing process diagnosis, product design, and development. The association rule modeling consists of four major parts including model attributes, items, item sets, and association rules. Frequent discovery items set findings among large data sets, and a typical example of the target problem is market basket analysis. The main two advantages of association rule modeling are the ability of the indexing and query processing, and the ability to exploit the database management system for scalability, checkpointing, and parallelization (Tan and Others 2007). Association rule algorithms fall into three main categories including multilevel, multidimensional, and quantitative.

- **Association Rule:** The association rule was introduced by Agrawal, Imielinski, and Swami (Agrawal *et al.* 1993a), and it is most commonly used for supermarkets to find buying patterns. In the beginning, it was adopted to find regularities in the shopping behavior of customers and then was applied to several application domains. In general, it is a tool to understand customer habits by finding frequent patterns, associations, correlations, or causal structures among datasets. The association rule is an unsupervised learning technique to discover all rules in the data set that meet some minimum support and minimum confidence constraints (Agrawal *et al.* 1994). The association rule has been used as a vital module of several recommendation systems, and sometimes it is referred to as frequent set mining. It has also been widely used in online retail stores, web usage mining, traffic accident analysis, intrusion detection, market basket analysis, bioinformatics, and so on (Wang *et al.* 2015). The method is also influential in identifying strong and exciting relationships between variables in a dataset using different measures of interest. To conclude, it is a common technique for market analysis that tries to find sets of frequently purchased products or a shopping cart containing particular items that are bought together. It is a useful tool for analyzing and predicting customer behavior to identify new opportunities for cross-selling products to the customers, and the famous example of this is the rule of diapers and beer.

1.1.1.1 Combination Modeling

No single algorithm or technique works best across all types of datasets and problems. Therefore, the choice is governed by the problem area, research objective, data preprocessing techniques involved, performance evaluation criteria, security and privacy, data integrity issues, and the critical aspects of the dataset being used. In some cases, due to the complex nature of the problem and multi-objective problem, which cannot be solved using standard techniques, the use of more than one approach together seems to be the right solution (Mukhopadhyay *et al.* 2014a). One study highlighted the importance of building a new combination methodology for solving the challenges and limitations of the traditional approaches for data analysis (Yang and Wu 2006). One of the advantages of hybrid models is providing accurate results and hence that are used more in the area of credit rating and stock-market prediction (Jadhav *et al.* 2017). This approach highlighted the fact that unless subjected to sufficiently rigorous tests entailed by hybrid techniques. Thus, a combination of data mining models is sometimes required to solve problems that are more complex and get better results. This approach may be necessary to have a multi-step process, which leads to new techniques such as CART (Classification and Regression Trees). The CART is the Classification and Regression Trees method, which is one of these companion methods.

- **Classification and Regression Trees (CART):** This is a nonparametric statistical procedure that identifies mutually exclusive and exhaustive subgroups that share common characteristics that control the dependent variable. The method was introduced in 1984 (Lawrence and Wright 2001). The CART is a binary method characterized by recurrence or repetition partitioning procedure capable of processing continuous and nominal attributes in both targets and predictors using a decision tree learning technique that outputs either classification or regression tree. It has three main elements including rules for splitting data, stopping rules for deciding, and prediction for the dependent variable. It is an inherently non-parametric supervised learning technique, since it is provided a labeled training dataset to construct the classification or regression tree model and intended to produce a sequence of nested, pruned trees. One of the significant advantages of CART is the capability for handling missing values (Wu *et al.* 2008). One can measure the results accuracy of a C&R tree by using an average squared error. A study found that CART has a better than average correct classification rate in comparison with discriminant analysis, logistic regression, and neural networks (Ince and Aktan 2009). Despite the drawbacks of CART techniques, such as it only considers a single independent variable on the dependent variable, and it grows the trees into multiple levels which can result in non-important splits, CART is a promising research tool and plays an essential role in the analysis of data collected for surveillance purposes (Lemon *et al.* 2003). Additionally, studies noted that even though there are other types of decision tree methods such as Quick, Unbiased, Efficient Statistical Trees (QUEST) and Chi-square-Automatic-Interaction Detection (CHAID), the CART is considered to be the best decision tree method since it is more likely to select the independent variable that is most different with respect to the dependent variable (Dan and Colla 1995, Lemon *et al.* 2003). In conclusion, the CART is easier to understand and relatively simple to interpret for non-statisticians, and it is a relatively 'automatic machine learning' method. The CART procedure examines all possible variables, independent or splitting, and selects the one that results in binary collections that are most different concerning the target variable, based on a predetermined splitting criterion.

In conclusion, data mining includes data collection and managing data. Analysis and prediction enable managers and businesses to understand the patterns hidden inside past data. It is evident from the literature that there are many data mining approaches. Although each method offers advantages and disadvantages, they are beneficial in different ways for planning and launching new marketing campaigns promptly. They are cost-effective in achieving customer satisfaction. Data mining can also be used to help improve the quality of the data, understand its semantics, provide intelligent querying functions, and so forth. Additionally, the last section leads us to think about the opportunities for integrating data mining techniques with DEA.

2.4.2.5 Integrating Data Mining with DEA

In general, the compelling feature of data mining helps companies to turn customer data into valuable customer-profiling information (Rygielski *et al.* 2002). From the literature above, some studies combined the two approaches to fill the gaps in both methods. Thus, an in-depth literature survey of data mining techniques and applications pointed out that developing data mining techniques is tending to become more expertise-oriented and problem-centered (Liao *et al.*

2012). Moreover, the authors emphasized the importance of integration of qualitative and quantitative methods which help to increase understanding of the subject of problems. Therefore, in this section, the opportunities to integrate data mining techniques with DEA are studied. We can divide this into two main parts, which are DM to help DEA and DEA to help DM.

2.4.2.5.1 DM to Help DEA

DEA does not have simple model performance metrics such as R^2 which sometimes give people the impression that simply generating DEA results makes for a meaningful analysis, but this is not the case. The analyst should take other steps for validation and the results should be carefully reviewed. Thus, many studies proposed the idea of integrating DEA with data mining, which helps to discover the remaining hidden patterns and essential insights into DEA results. For example, a study suggested an integrated framework between DEA and text mining for the identification and exploitation of a new business area using patent information (Seol *et al.* 2011). Another study combined the K-Means algorithm with DEA to reduce the numbers of variables in the DEA model (Lemos *et al.* 2005). To making the information more understandable and interpretable, a study developed a general decision support system framework to analyze the results of DEA models through data visualization (Akçay *et al.* 2012).

Additionally, Emrouznejad and Anouze proposed a combined framework to understand the market share's impact on efficiency when based on multi-factors (Emrouznejad and Anouze 2010). They used the obtained efficiency scores by DEA, which were divided into two efficient and inefficient groups, as a target value for C&R tree analysis to explore the impact of internal and external factors. This integration of DEA with classification and regression analysis helps to discover the reasons behind efficient and inefficient DMUs.

2.4.2.5.2 DEA to Help DM

On the other hand, other studies used the DEA method to support data mining techniques to get more insights. For instance, Toloo, Sohrabi, and Nalchigar proposed a new method for ranking association rules by the integrated Data Envelopment Analysis (DEA) model, which can find the most efficient association rule for market basket analysis (Toloo *et al.* 2009). Chen integrated the DEA method with association rules of data mining to provide more insights into the rules discovered (Chen 2007b). From another point of view, Nakhaeizadeh and Schnabl used DEA to evaluate several data mining algorithms considering positive and negative characteristics of DM-algorithms (Nakhaeizadeh and Schnabl 1997). Some research compares the DEA approach with some data mining techniques and provide the differences between the two alternative methods. Athanassopoulos and Curram made a comparison of two non-parametric methods, DEA and artificial neural networks, which are pursued at two levels. The first level is the ability to disentangle efficient and inefficient units in a controlled experiment, and the second is to give useful managerial insights concerning the performance of individual branches (Athanassopoulos and Curram 1996). In the next section, the DEA and DM comparison are provided to conclude this work.

2.4.3 Other Methods

In the last decades, there has been a rapid growth of operations research techniques that help firms to maintain their production activities in industrial manufacturing enterprises all the way to service providers. However, there are a wide variety of techniques and methods that have been utilized in the measurement and analysis of productive efficiency. In the context of technical efficiency measurement, there are varieties of approaches which are generally categorized as either stochastic and deterministic methods or parametric and non-parametric methods. There are two categories of Multiple Criteria Decision-Making (MCDM) problems, which are multiple criteria discrete alternative problems and multiple criteria optimization problems. Under these two categories, there are several methods and techniques for solving multiple alternative problems. In this section, we study some of the well-known methods and try to summarize the features and limitations of each one compared with the primary method of this research (DEA).

2.4.3.1 Free Disposal Hull (FDH)

FDH is a non-parametric method to measure the efficiency of production DMUs, and it is considered an alternative approach to DEA for efficiency measurement. In other words, FDH can be seen as a similar approach of the DEA model with variable returns to scale, and the estimated efficiency frontier is not required to have a convex shape. Researchers introduced the FDH model (Deprins and Simar 1984) which was further developed by (Lovell *et al.* 1994). Tulken extended FDH by presenting a mixed-integer linear programming formulation. (Tulkens 1993) Leleu (Leleu 2006) furthered this with a complete LP framework to deal with all FDH models. In the context of the traditional methods that were developed for estimating returns to scale, Kerstens and Vanden Eeckaut developed the FDH to be suitable for all reference technologies (Kerstens and Vanden Eeckaut 1999).

The FDH model is driven by the assumption of the free disposability to obtain the production possibility set (Lim *et al.* 2016). It simply assumes that if a unit uses a certain amount of inputs to produce a certain amount of inputs, additional inputs would not hurt the output (inother words, the extra inputs could be freely disposed of.) Similarly, the same unit, using the original level of inputs could produce the less output (perhaps by freely disposing of the excess outputs.) The FDH model does not assume convexity of production possibilities. The comparison does not use hypotheses and/or unreal observations. It only assumes what can be done based on the actual observed performance (Benslimane and Yang 2007). FDH determines a set of relatively efficient units, just like DEA, just with a different set of assumptions and relaxing convexity. Studies adopted FDH evaluation the technical efficiency of the provision for municipal services (De Borger *et al.* 1994), banks (Borger *et al.* 1998), and for a business-to-business transaction (Benslimane and Yang 2007). Furthermore, Agrell extended the links between the non-parametric FDH and DEA models (Agrell and Tind 2001), where they derived a linear program for the FDH model but without returns to scale assumptions and with a radial output distance function. While FDH models aim to minimize inputs or maximize outputs, the FDH model obtains the production possibility set by defining it differently with CCR and BCC models (Lim *et al.* 2016).

2.4.3.2 Stochastic Frontier Analysis (SFA)

There is another category to measure economic efficiency, which is a parametric method and includes the Stochastic Frontier Approach (SFA), the Thick-Frontier Approach (TFA) and the Distribution-Free Approach (DFA). The non-parametric methods analyze input and output data, while the parametric methods analyze inputs and outputs based on reactions to market prices. In this section, I am going to talk about popular parametric methods in which SFA assumes two error elements, and inefficiency is considered to have an asymmetrical distribution.

The SFA method deals in general with the problem that not all deviations from ideal performance are due to inefficiency. It estimates a parametric frontier of the best possible practices given a standard cost or profit function. The early works of the productivity analysis and the main focus of the methods for measuring efficiency that have been proposed by Aigner and Chu (Aigner and Chu 1968), Timmer (Timmer 1971), Afriat (Afriat 1972), Richmond (Richmond 1974), Schmidt (Schmidt 1976) were fundamental to develop SFA. The stochastic frontier approach was proposed by Meeusen and Van den Broek (Meeusen and Den Broeck 1977), and initially developed by Aigner, Lovell, and Schmidt (Aigner *et al.* 1977). It designs a parametric frontier from a standard cost or profit function, and it is one such technique to model producer behavior.

In the SF literature, several models have been developed for inefficiency estimation such as the flexible model (Kumbhakar 1990), the inefficiency models (Cornwell *et al.* 1990, Lee and Schmidt 1993), the time decay and inefficiency effects model (Battese and Coelli 1995), normal-truncated regular model (Wang 2002), simulated maximum likelihood (Greene 2003), and the fixed effects and random effects/parametric models developed by Greene (Greene 2005). Also, Battese and Coelli introduced a SFA function for unbalanced panel data (Battese and Coelli 1992). The stochastic frontier method combined a two-part error term. The first one of the disturbance terms is assumed to be normally distributed and to capture the random error. The second one of the disturbance terms reflects inefficiencies and is considered to follow several common distributions. In the basic stochastic model, the leading cause of any composite error term of the observed production from the microeconomic theoretical output is purely random disturbances and inefficiency (Chen 2007b). The SFA method produces efficiency estimates or efficiency scores of individual units. Thus, one can identify those who need intervention and corrective measures, and it is motivated by the idea that deviations from the production 'frontier' might not be entirely under the control of the firm being studied. The traditional random error and another related to the state of technical inefficiency are the main components of the stochastic frontier.

The method has been applied to a wide range of application areas and industries with various subjects such as for the airline industry (Cornwell *et al.* 1990), economic reforms (Cooper *et al.* 1995), the banking industry (Bauer *et al.* 1998, Greene 2005, Silva *et al.* 2017), the hospitality industry (Anderson *et al.* 1999, Chen 2007a), agricultural economics (Wadud and White 2000, Theodoridis and Anwar 2011), the healthcare industry (Jacobs 2001), the container port industry (Cullinane *et al.* 2006), and the energy sector (Lin and Wang 2014). Primarily, in the mobile telecom sector, it is used to measure the relative market potential, which helps to forecast the number of new mobile telecom generation subscribers (Lim *et al.* 2012). The SFA method relies on regression analysis to estimate a conventional cost function, but the efficiency of trust is measured using the residuals from the estimated equation. Thus, the literature shows that many studies addressed the comparison of SFA with DEA (Cooper *et al.* 1995, Bauer *et al.* 1998, Anderson *et al.* 1999, Wadud and White 2000, Jacobs 2001, Cullinane *et al.* 2006, Chen 2007a, Theodoridis and Anwar 2011). Even with the strengths and weaknesses associated with DEA and SFA, some studies found a high degree of correlation between the efficiency estimates derived from both approaches according to the Spearman rank coefficients (Cooper *et al.* 1995, Wadud and White 2000, Cullinane *et al.* 2006, Theodoridis and Anwar 2011). However, Chen concluded that the advantage of SFA over DEA was its ability to isolate the influence of factors other than inefficient behavior, which corrects the possible upward bias of inefficiency (Chen 2007b).

As a conclusion, SFA is a powerful tool for examining the effects of the intervention, and it assumes that a parametric function exists between production inputs and outputs. The strength of SFA is that it considers stochastic noise in data and allows for the statistical testing of hypotheses concerning production structure and degree of inefficiency, and it has the attraction of allowing for statistical noise. Theodoridis and Anwar indicated the main pros of SFA which are the ability to accommodate statistical noise, and the use of standard statistical tests (Theodoridis and Anwar 2011). These findings are similar to another study that pointed out the advantage of the SFA method in its ability in the decomposition of the residual into statistical noise and then efficiency effect (Silva *et al.* 2017). Moreover, Jacobs underlined that SFA has the benefit of allowing for statistical noise even with the disadvantage of requiring strong assumptions about the inefficiency term (Jacobs 2001). Theodoridis and Anwar mentioned the main cons, which are expressed in the sensitivity of the model to a priori assumptions, which required a pre-specification of the functional form and explicit distributional assumption for the efficiency (Theodoridis and Anwar 2011). At the same time, a study listed some of the disadvantages of SFA where it requires a specific functional form a priori, and where the method has an inductive bias in the stochastic process (Silva *et al.* 2017).

2.4.3.3 Analytic Hierarchy Process (AHP)

Saaty (1977) addressed the scaling ratios using the principal eigenvector of a positive pairwise comparison matrix to introduce the notion of a hierarchy for multiple criteria decision making. This work was the first step to introduce how the hierarchy could be a useful tool for decomposing an extensive problem. Later on, the AHP method was developed early in 1980 by Saaty, and he structured a decision problem as a hierarchy starting from the goal on the top and of a group of criteria that connect the goal to the list of alternatives (Saaty 1977). The method has been used for a wide range of decision-making in different domains such as government, business, engineering, and industry.

The AHP is one of the most popular methods for formulating and analyzing decisions using four steps: the structuring of the situation into a hierarchical model; making pairwise comparisons and obtaining the judgmental matrix; relating weights and consistency of comparisons; collecting the weights across various levels to achieve the final weights of alternatives (Zahedi 1986). In general, the AHP is a method of measurement using pairwise comparisons and relies on the expert judgments of the decision maker to derive priority scales.

The AHP approach is based on three main elements: starting with decomposing a complex problem into a hierarchy, using measurement methodology for establishing the priorities among the components within each level of the hierarchy, and using measurement theory for creating the priorities of the scale and consistency by the group of respondents (Wind and Saaty 1980). Additionally, several suggestions were discussed on how to combine the judgments of evaluators from the intuitive basis perspective, as determined by (Saaty and Vargas 1980), and from a theoretical point of view as determined by (Vargas 1982, Aczél and Saaty 1983). These perspectives initiated a robust estimating method of AHP called the mean transformation (Zahedi 1986) along with the geometric mean method (Crawford and Williams 1985) for estimating ratio-scaled priority values from reciprocal pairwise comparison judgment matrices. These two methods became the top best methods for future research and comparative studies in diverse areas. Later on, Saaty did some axiomatic treatment for the method including the reciprocal property, homogeneity, dependence, and expectation of the outcomes to successfully cover decision making in complex social and political problems (Saaty 1986).

In addition, Saaty introduced a consistency index to measure the subjective evaluation of the decision maker (Saaty 1990). While the AHP initially covered problems in portfolio decisions management, new product development, and mixed marketing strategies (Wind and Saaty 1980), the method was developed further to include other applications dominant in manufacturing and followed by the environmental management and agriculture field, the power and energy industry, the transportation industry, the construction industry, the healthcare industry, and other areas (Sipahi and Timor 2010). Moreover, there has been broad implementation of the AHP in different fields mainly on strategic decisions within operations management, product, and process design; planning and scheduling resources; project management, and supply chain management (Subramanian and Ramanathan 2012).

The method was tested in a real-life case with a multimedia authoring system in a group decision environment for product adoption, and the author found the AHP more helpful for consensus building in group decision settings as well as relevant and useful for in-group decision support (Lai *et al.* 2002). The AHP has successfully been applied to many applications and problems of diverse scientific fields such as for solving the MCDM problem (Majumdar *et al.* 2017), checking the suitability of a landfill site (Majumdar *et al.* 2017), managing information systems (Oztaysi 2014), and integrating the evaluation of Landfill Site Sensitivity Index and Economic Viability Index to evaluate a complex and protracted process of landfill site selection (Majumdar *et al.* 2017).

In particular, the AHP method has been integrated with other approaches to consolidate the results of complex problems. For instance, the AHP was used with Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for hazardous waste management, which used fuzzy-AHP weights in the TOPSIS method to make the application more realistic and reliable (Saaty 2008), and also was combined to a TOPSIS-Grey technique for determining the weights of the decision criteria (Oztaysi 2014). In another study (Aragones-Beltran *et al.* 2014), the AHP was combined with the analytic network process (ANP) for solar power investment.

In terms of DEA, a study (Mohajeri and Amin 2010) used the AHP with DEA for selecting the most preferred railway station. Moreover, another study used the AHP to replace a super-efficient in the DEA model (Jablonsky 2007) that aimed to evaluate the efficiency of the production process. The strength features of the AHP are its ability to consider the subjective judgments of decisionmakers, which makes very attractive for integrating with other methodologies (Subramanian and Ramanathan 2012), and its mathematical simplicity and flexibility (Sipahi and Timor 2010). Based on this knowledge, researchers precisely described the features of the AHP as follows: the ability to handle both tangible and intangible information in the decision process, the structure of a group decision and focus on the objectives, and the capacity to continue discussion until all aspects are covered. In this context, the argument that the AHP can help structure complex decisions and improve measures of service is evident (Dyer and Forman 1992).

A lingering concern in the AHP mathematics is how intangibles might be measured (Saaty and Mwambi 2013). A critical point is that one of the limitations with the AHP is the weights dependency since it is initially first to be composed concerning all such criteria before normalized for the AHP (Saaty 1990). Thus, there is no guide on the outcome of manipulations since there is no standard scale in contrast such as some criterion that was measured in dollars and used to select the best alternative. Saaty also addressed the concern of improving consistency by derived priority scales since the inconsistency that might happen from judgments (Saaty 2008).

2.4.3.4 Analytic Network Process (ANP)

The ANP, first proposed by Saaty, was considered an extension of the analytic hierarchy process (AHP), capable of handling the interdependencies issue among different criteria (Saaty 1996). In other words, the ANP appears more realistic in certain situations where criteria are dependent internally. The main difference between the AHP and the ANP is that the ANP does not have designed levels as in a hierarchy, which permits both interaction and feedback within criteria and between clusters. Saaty and Vargas introduced the main four main steps of ANP: constructing the model and structuring the problem, making the pairwise comparison matrices and priority vectors, forming the super matrix, and selecting the best alternatives (Saaty and Vargas 2006). The criteria and alternatives are grouped into clusters and known as elements.

Mainly in the ANP, the network has two elements which are the criteria and sub criteria that control the interactions and influences among the components and their clusters. In complex problems, using the ANP can be an advantage, and the factors have the flexibility to control, and be controlled by, the different levels or clusters of adjectives. Also, the ANP can handle two-way arrows or arcs, which represent the interdependencies among different levels of criteria. Due to the interaction of higher-level elements with lower-level elements in the hierarchy, there are many difficulties with structuring in a hierarchical structure. The ANP has a feedback structure that looks more like a network. Loops and cycles connect the components of elements without levels (Saaty 2013). In addition to quantifying factors and incorporating managerial preferences, the ANP technique helps the decision-making process for management by structuring the decision environment into a logical relationship in numerous ways (Khadivi and Fatemi Ghomi 2012): for the maintenance performance indicator selection (Van Horenbeek and Pintelon 2014), for supply chain management (Chen *et al.* 2012, Amlashi 2013), for environmental protection issues (Kuo and Lin 2012), for information system project selection (Lee and Kim 2000), for selection of a logistic service provider (Jharkharia and Shankar 2007), and for contemporary manufacturing (Vinodh *et al.* 2011). While the method has been used in several applications, especially to study risk and uncertainty, researchers predicted an opportunity for the ANP to be used in many domains in the future (Sipahi and Timor 2010).

Additionally, the method was combined with other methods such as the grey relational analysis to study the environmental protection and green supply chain management (Hashemi *et al.* 2015), with the AHP for selection of the solar power investment (Aragonés-Beltrán *et al.* 2014), and with the Quality Function Deployment (QFD) to help address the issue of paucity of awareness and quit implementing Quality Systems (Amlashi 2013). Also, the AHP was integrated with DEA to provide more consistent results by setting up criteria weight preferences or high-tech industry (Kuo and Lin 2012). It can be challenging to determine the weights, but helpful for the validation process. Thus, it integrated with DEA for personnel selection in human resources management (Lin 2010) and facilities location (Khadivi and Fatemi Ghomi 2012).

The main advantage of the ANP is that it provides a flexible model to solve complex real-world situations and has the ability to consider all kinds of dependence and feedback on the problem (Sipahi and Timor 2010). Also, the ANP has dynamic characteristics that make it a handy tool in a complex decision-making environment (Hashemi *et al.* 2015), and it offers a more consistent ranking compared with the AHP (Kuo and Lin 2012). The ANP is recommended when there are interdependencies among groups of criteria and alternatives (Aragonés-Beltrán *et al.* 2014). Moreover, the ANP is a recommended tool since it considers mutually influential factors and deals with both tangible and intangible factors (Chen *et al.* 2012). It is qualified to take into consideration both qualitative and quantitative criteria. Besides the traditional ANP (which has some limitations including crisp decision-making, unbalanced judgment scale, imprecise and subjective judgment, and uncertain decision-making), there is also a fuzzy ANP that was created to overcome these limitations (Vinodh *et al.* 2011). One of the limitations of this technique is the difficulty in identifying the criteria that will influence others and the relative intensity of influence (Aragonés-Beltrán *et al.* 2014). Thus, whenever any alternative changes, all the influences where this alternative participates would also change.

2.4.3.5 Hierarchical Decision Model (HDM)

The HDM was introduced and developed by Kocaoglu (Kocaoglu 1983). The HDM is a multi-criteria tool to quantify and incorporate quantitative and qualitative judgments that help decision makers. Basically, in this method, the final decisions gained are based on the local contributions by evaluating the last ranking of alternatives (Chen and Kocaoglu 2008). The HDM methodology depends on three main steps: hierarchical decision modeling that includes objectives, criteria, and alternatives; the selection of an expert panel to make the pairwise comparison; and a research instrument to get reasonable and balanced results. In other words, the method needs four main processes including the development of definitions and qualitative relationships, a dry run with the program management team, the selection of an expert panel, and some panel meetings to build the decision model (Kocaoglu 1983).

The HDM approach is taking work from the Analytic Hierarchy Process Approach, and it has been used widely in multiple applications such as determining the innovativeness of the company (Phan 2016), selecting target markets of healthcare device (Sheikh *et al.* 2016), identifying the best alternatives to help the diffusion of teleconsultation in healthcare (Alanazi *et al.* 2015), assessing healthcare technology (Hogaboam *et al.* 2014), managing product life cycles (Eastham *et al.* 2014), evaluating the effectiveness of energy policy (Abotah and Daim 2017), and also for daily life decisions such as choosing the most desirable car characteristics (Saatchi *et al.* 2013). Some studies integrated other methods to fill the gaps in the HDM. For example, the Technology Acceptance Model is used to increase the successful adoption of the teleconsultation diffusion model (Alanazi *et al.* 2015) while Delphi method is used to measure the indicator evaluation for specific industries (Phan 2016).

Researchers highlighted the significant actions that the HMD provides in the analysis process starting with structuring the decision problem into levels, making the pairwise comparison to elicit decision maker's preferences, calculating the priorities of the objectives, and finally checking the consistency of the decision maker's responses (Hogaboam *et al.* 2014). Recently, Abbas and Kocaoglu defined the acceptable limits of inconsistency and established consistency thresholds with a significance analyzing for inconsistency in the HDM (Abbas and Kocaoglu 2016). Sheikha, Kima, and Kocaoglu highlighted some critical points that were gained with the process of building the model. They cover the implicating preferences that were stated and became elements for comparison, comparing long-term and short-term objectives, developing objectives and decision elements within a non-threatening environment, and involving both strategic and operational perspectives (Sheikh *et al.* 2016). Thus, they listed the advantages of the HDM as simplifying the complexity of decisions by maintaining the accuracy of capturing judgments, as a guide in strategic planning, and providing opinions and framework for decision trends and sensitivity analysis. Furthermore, Chen and Kocaoglu emphasized managing a sensitivity analysis (SA) for the HDM results to address the various contingencies (Chen and Kocaoglu 2008). The HDM offers up significant information in each level of comparison between the objectives, criteria, and alternatives, including the inconsistency and disagreement among the experts, which validates the accuracy and provides valuable insights into the expert's opinions to assess the importance of the results.

2.4.3.6 Fuzzy Cognitive Map (FCM)

The FCM is a method for a cognitive map that shows the social scientific knowledge and relationship among mental landscape components, and it is a useful tool for decisional processes. The method was developed by Kosko (Kosko 1986) to capture causal knowledge and processing computational inference in directed graphs. The initial idea of the cognitive map was found in the 1940s by Tolman (Tolman 1948). Later on, Axelrod introduced the cognitive maps approach for representing social scientific knowledge (Axelrod 1976). The method has originated from the integration of fuzzy logic and neural networks (Papageorgiou and Salmeron 2013). Based on the expert's knowledge in the field, the causal weighted digraphs are assigned to set of signs between every two concepts to show causal relationships among concepts in the graph. The causal relationship between different concepts has three options: positive (direct relation), negative (inverse relation) or no causality (no relation between the two concepts) (Stylios and Groumpos 2004, Azadeh *et al.* 2015). These are used as factors to calculate the strength of the impact of these components, which in turn are used to assist the causal knowledge augmentation procedure. The nodes represent concepts of the problem, and the edges clarify cause-effect relations among the concepts. The main components in the FCM graph are nodes, which describe the concepts of behavioral characteristics and weighted arcs that represent the causal relationships among concepts (Stylios and Groumpos 2004).

In using the FCM structure, it is straightforward and easy to understand which concept influences others and what the degree of influence is (Stylios and Groumpos 2004). It is easy to develop the model for a nontechnical audience. A group of authors proposed a learning algorithm with the FCM based on Particle Swarm Optimization (PSO) to reach the constant state using suboptimal weight matrices. The new concept was introduced by the functional representation of FCMs (Parsopoulos *et al.* 2003). Codara pointed out the primary functions of the method which are explanatory for understanding the reasons and representation of the situation, predictive for future decisions and actions, reflective for introducing the necessary changes, and strategic for generating the accurate description of a complex problem (Codara 1998).

Furthermore, the FCM method was recommended to represent human and knowledge experience since it is displaying the cause and effect relationships between the concepts of the problem (Azadeh *et al.* 2015). This method is widely used to represent social scientific knowledge and learning procedures (Parsopoulos *et al.* 2003), complex social systems modeling (Taber 1991), modeling complex systems (Stylios and Groumpos 2004), product planning (Jetter and Sperry 2013), decision support in network security and intrusion detection

(Siraj *et al.* 2001), lean production assessment (Azadeh *et al.* 2015), and calculation in healthcare systems (Rezaee *et al.* 2018). Additionally, it was integrated successfully with DEA for determining the factors of leanness assessment and optimization (Azadeh *et al.* 2015) and for drawing relationships between the efficiency concepts of inputs and outputs (Rezaee *et al.* 2018).

Practically, the FCM is a useful tool to explore and evaluate the input effect on dynamic systems. The FCM is considered a simple form of recursive neural networks since it allows feedback loops (Jetter and Sperry 2013). It is a helpful technique to manage the problems that have unsupervised data (Azadeh *et al.* 2015). The method has several advantages which Papageorgiou and Salmeron describe as easy to build and use, flexible in representation, easily understood by non-technical experts, ready for low-time performing, and capable of handling complex issues and dynamic effects (Papageorgiou and Salmeron 2013). Also, one of the main advantages of the FCM is the ability to handle incomplete or conflicting information since most real-world problems may have steps that include such problems (Azadeh *et al.* 2015). On the other hand, the traditional FCM has several limitations including lack of time delay; the linearity of edges' weights; lack of symmetry and non-monotonic logic of a causal relation; the inability to handle multi-meaning environments; quantitating the concepts; relationships between nodes; present logical operators among nodes; and handling the randomness in complex domains (Papageorgiou and Salmeron 2013). However, several extensions have been proposed to overcome these limitations.

2.4.3.7 Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS is a multi-criteria decision analysis approach, which is based on the selection of an alternative principle that is the closest to the positive ideal solution and farthest away from the perfect negative solution. The method was developed by Hwang and Yoon (Hwang and Yoon 1981), and further developments by Yoon (Yoon 1987, Hwang *et al.* 1993). To rank the DMUs, the method first constructs a normalized decision matrix to facilitate the comparisons across criteria and a weighted normalized decision matrix to determine the ideal solution. Then the separation measures and the relative closeness for each DMU to the perfect solution are calculated. In other words, it assumes that the best alternative should have, with one another, the shortest distance from the positive-ideal solution and the farthest distance from the negative ideal solution. The method can handle all types of criteria including subjective and objective criteria, and the computation processes are simple and understandable. The TOPSIS technique is practical and useful for ranking and selection of the best alternative(s).

The TOPSIS method has received much interest from researchers and practitioners. It is widely adopted to solve a severe problem including network interface selection of mobile wireless communication networks (Senouci *et al.* 2016), computing performance efficiencies (Chitnis and Vaidya 2016), supply chain selection management (Boran *et al.* 2009), location problem (Yoon and Hwang 1985), interval data problems (Jahanshahloo *et al.* 2009), fuzzy like interval-valued (Ashtiani *et al.* 2009), and decision environment issues (Chen 2000, Shih *et al.* 2007, Gumus 2009). Many studies compared and combined the TOPSIS with other methods, specifically the fuzzy set approach, to enhance the ranking results of the DMUs (Boran *et al.* 2009, Behzadian *et al.* 2012). Additionally, there are many studies that combine the TOPSIS theory with applications to enhance motivation for categorizing applications. For instance, it is united with the AHP to determine the most suitable CMS alternative for information systems and to improve uncertainty in practical ways (Oztaysi 2014). It is used to examine the context of supplier-selection decision making (Lima Junior *et al.* 2014). It was integrated with the neural network to produce a model to assess the relative efficiency for banking performance with the active predictive ability (Wanke *et al.* 2016), and with GLMM-MCMC methods to evaluate the impact of contextual variables on performance (Wanke *et al.* 2015).

Regarding DEA, the literature focuses on adopting both methods together. For instance, it was used to address the issue of assigning a unique rank to the DMUs in the DEA method and improve the performance evaluation process in a business situation (Chitnis and Vaidya 2016). In some studies, the TOPSIS approach was used to modify the DEA cross- efficiency method by solving the different optimal weights (Jahanshahloo and Abbasian-Naghneh 2011), and to resolve the second phase of introducing the cross-efficiency to improve the ranking approach (Wu *et al.* 2013). Despite the similarity of the TOPSIS method and DEA in the idea of maximized outputs or minimized inputs, the TOPSIS approach essentially determines the weights relative to the importance of each factor while DEA defines the weights within the model (Wanke *et al.* 2015). This approach can be one of the points to extend my research in the future.

One author introduced the idea that it is easy to define an ideal solution by assuming each attribute takes increasing or decreasing variation. In general, the TOPSIS is a method that can handle performance rating values and the weights of criteria that are linguistics terms (Ashtiani *et al.* 2009). It removes the concern of the DM in choosing a particular method for ranking. In addition, it provides high accuracy compared to other MADM algorithms (Senouci *et al.* 2016), it deals with uncertainty (Boran *et al.* 2009), and it does not require attribute preferences to be independent (Behzadian *et al.* 2012). The TOPSIS approach uses a vector normalization concept that helps to eliminate the units of criterion functions (Opricovic and Tzeng 2004) with the fewest rank reversals (Shih *et al.* 2007). On the other hand, one of the limitations of this method is that the relative importance of the distances between the two reference points is not considered (Opricovic and Tzeng 2004). Also, human factors can create bias in the traditional

TOPSIS since the method needs to determine the weights of evaluation indicators in the beginning (Wu *et al.* 2013). The TOPSIS and most of MADM's techniques suffer from ranking abnormalities which can potentially decrease the quality of the results. However, a study in 2016 provided a detailed analysis regarding minimizing the normalization effect on the rank order (Senouci *et al.* 2016).

2.4.4 Compare and Contrast

Research by Koopmans, Debreu, and Farrell was the basis of most of the economic theories that address the activity and efficiency analysis. During the last few decades, efficiency estimation studies have been extended to explore a different level of efficiencies across the production process. Opricovic and Tzeng included the main steps of multi-criteria decision into establishing system evaluation criteria, generating alternatives, evaluating the alternatives in terms of the criteria, applying an appropriate multi-criteria analysis method, accepting the optimal alternative(s), and finally gathering new information for the next iteration of the multi-criteria optimization (Opricovic and Tzeng 2004). Multi-criteria tools cannot replace the decision maker's preferences but can help to manage them. They can help the decision-maker to reflect on them, to analyze the outcomes, and can help practitioners find the best methods and model to solve an issue. The techniques can handle a variety of different and conflicting criteria for selecting, evaluating, assessing, and ranking among predetermined decision alternatives to help decision-makers solve complex decision situations involving multiple criteria. Several methodologies and algorithms have been proposed and developed in this field and most of them are categorized into multiple-criteria decision analysis (MCDA) or multiple-criteria decision-making (MCDM). The MCDA has three main types of decision analysis: choosing the best alternative, sorting the alternatives into groups, and ranking the alternatives from best to worst.

The MCDM was categorized and divided into another two groups called multi-objective decision making (MODM) and multi-attribute decision-making (MADM) (Clímaco 1997, Wallenius *et al.* 2008). The MODM methods are used for many real-world decision-making problems that have more than one goal (objective), and they account for multiple goals for promising future directions. On the other hand, Multi-Attribute Decision Making (MADM) techniques are approaches for evaluating multi-criteria simultaneously that are used to determine the optimal alternative among several alternatives. Most of the ranking MADM's techniques rely on different normalization and upper/lower bounds to eliminate dimensional unit differences among the criteria. From another point of view, studies are grouped into two main approaches. The most know parametric approach is the stochastic frontier approach (SFA), and the most notorious nonparametric approach is DEA.

Singh, Motwani, and Kumar categorized the productivity measurement approaches to three main groups: index measurement, econometric models, and linear programming that constructs a production frontier—the most common programming procedure for productivity changes being the DEA method (Singh *et al.* 2000). Solving the problem can be interpreted using different methods, but getting the best results needs the best approach. To prove that DEA is a robust and useful tool to identify the efficiency of the DMUs in this research, and to achieve overall comparability among the methods, the comprehensive comparison with the data mining techniques and MCDM approaches are adopted in this section.

2.4.4.1 Data Mining and DEA Comparison

Cios and Kurgan pointed out one of the significant difficulties in data mining is that many techniques are available to the practitioners (Cios and Kurgan 2005) and one of the challenges is how to mine uncertain and incomplete data (Chen *et al.* 2015). At the same time, data mining techniques have several advantages. One of the main objectives of data mining is to produce exciting rules concerning some user's point of view (Toloo *et al.* 2009). One study (Mukhopadhyay *et al.* 2014b) pointed out that the primary objective of any data mining activity is to build an efficient predictive or descriptive model using data that can be generalized to new data. Also, most of the data mining techniques are not suitable for analyzing unstructured data (Seol *et al.* 2011). While most of the algorithms that are used for data mining techniques use numeric data and tend to be very mathematical, methods for data mining are fundamentally different from traditional statistical analysis.

The study of (Bowlin *et al.* 1984) was the first research to compare DEA with data mining methods, regression, using artificial data which was later replicated and extended by Thanassoulis (Thanassoulis 1993) to get more insights. Later on, Athanassopoulos and Curram did similar work as a comparative study of the differences between DEA and artificial neural networks using a set of commercial bank branches data. Moreover, Pendharkar, Khosrowpour, and Rodger compared DEA with another data mining method, Learning Bayesian networks, for which they used real data for discovering breast cancer patterns. They found that both could be a tool for binary classification problems (Pendharkar *et al.* 2000). To provide a clear picture, I take two of the well-known data mining techniques, which are the regression and neural networks, and I try to do an in-depth comparison with DEA in this section. Thanassoulis pointed out that regression is a parametric method that requires specifying a customary model for the relationship between inputs and output level (Thanassoulis 1993). While both DEA and regression deal with shortcomings and deficiencies of the ratio analysis, one of the advantages of regression over DEA is the statistical significance tests (Bowlin *et al.* 1984). Use of DEA distinguishes among DMUs and includes some indicators to improve the inefficiency whereas the regression does not (Bowlin *et* *al.* 1984).. A study later summarized the advantages of DEA over regression (Thanassoulis 1993) as the following:

- DEA does not require hypotheses
- DEA measures efficiency against the best, not against the cloud of average performance
- DEA identifies the nature of returns to scale and the efficient boundary
- DEA allows for variable marginal values for different input-output mixes
- DEA provides a specific reference set for each inefficient unit
- DEA is natively able to handle multiple inputs and multiple outputs simultaneously
- DEA allow outputs and inputs to be independent of one another
- DEA provides more accurate targets because it is a boundary method. On the other hand, Thanassoulis also listed advantages of RA over DEA.
- RA gives a better predictor of future performance, but the new DEA approach for technology forecasting called TFDEA gives better results than the multiple-regression forecast in some cases (Inman *et al.* 2006).

- Estimates of relative efficiency are more transparent and can be more readily communicated, but also the scores of efficiencies for the DMUs that DEA provided are very simple and understandable.

- RA offers greater stability of accuracy, but DEA exceeds regression on the accuracy while regression provides an average performance rather than estimates on efficiency.

- RA offers the ability to estimate confidence intervals and test assumptions while this is an ongoing research area in DEA (Barnum *et al.* 2008).

- DEA estimates of marginal values and target levels are not affected by correlations and multicollinearity. However, regression is less likely to give extreme inaccuracies of estimates at the individual DMU level.

2.4.4.2 Other Methods and DEA Comparison

To adopt an effective and efficient model and analysis, I studied other suitable methods. Based on the in-depth literature review of the selected methodologies, Table 2.4 shows a summary of the advantages and disadvantages of each method based on the steps of the research. Zelany pointed to solving problems by simplifying how to choose the best method by identifying the objectives criteria of the research (Zelany 1974). Based on the main features that my research questions, and to fill the objectives of this research in a comparison framework, I can say that DEA is the most suitable method for my research.

TABLE 2.4: SUMMARY OF ADVANTAGES AND DISADVANTAGES OF ALL METHODS BASED ON RESEARCH STEPS

Methods	Research Object	Research Data	Research Factors	Research Analysis	Research Results
DEA	Sorting	Quantitative and based on numerical data	No limits to the number of inputs and outputs and unlimited DMUs	Flexible (with or without weights)	Provide reference sets for benchmarking
FDH	Sorting	Quantitative and based on numerical data	No limits to the number of inputs and outputs and unlimited DMUs	Flexible (with or without weights)	No best practice (compared with a real unit)
SFA	Sorting	Quantitative and based on numerical data	Inputs and outputs based on reactions to market prices	Flexible (with or without weights)	Best possible practices are given a standard cost or profit function
AHP	Choosing, Evaluating, and weighting	Qualitative and based on expert judgment	Can handle a limited number of factors and limited alternatives	Works with weight only	Comparison between the objectives, criteria, and alternatives
ANP	Choosing and weighting	Both qualitative and quantitative criteria	Efficiently handle large combinatorial problems without oversimplification	Given Alternatives can influence the weighting of criteria	Difficult to identify influence and relative intensity of influence of the criteria on others

HDM	Choosing and weighting	Quantitative and qualitative judgments	Can handle a limited number of factors and limited alternatives	Works with weight only	Comparison between the objectives, criteria, and alternatives
FCM	Modeling and exploring	Qualitative and Based on the experts' knowledge	Nodes represent concepts of the problem and the edges clarify cause-effect relations among the concepts	The causal relationship between different the concepts required	Represent the causal relationships among concepts
TOPSIS	Ranking	Quantitative and based on numerical data	Subjective and objective criteria	Needs to determine the weights of evaluation indicators	The separation measures and the relative closeness for each DMUs to the ideal solution are calculated

Chapter 3 Gap Analysis

A deep literature review on the efficiency measurement in the cellular telecom industry, and more specifically on quality management and BTS performance, was conducted. This leads to the identification of several significant gaps. Based on the key gaps in the literature, the goals needed to fill this gap are considered. Finally, to achieve the research goals, the research questions were addressed. Figure 3.1 shows the research gap analysis including the research gaps, goals, and questions.

FIGURE 3.1: THE RESEARCH GAP ANALYSIS

3.1 Research Gaps

Based on the literature review, it is clear that most previous researchers were focused on individual factors in the BTS field. This leads us to the first gap in the literature, which is a limited study on evaluating and prioritizing the technical efficiency of the BTS. From a practical perspective, it is hard to compare multiple

BTSs with many KPIs to prioritize the BTS based on efficiency. However, there is a need to identify a comprehensive way to understand the efficiency gap for insufficient mobile sites, and to spend more effort on this gap to achieve the industry regulatory service and global KPIs standard. Data Envelopment Analysis (DEA) has been used in various industries to measure the efficiency of Decision-Making Units (DMU). However, a comprehensive literature review was conducted to address the gaps in implementing the DEA method in the telecom industry and the mobile sector. Most of the studies focused on comparing the companies either in the same country or in different countries from a financial perspective and others from a customer satisfaction point of view. As a result, the second research gap was identified, which is the lack of robust tools in the mobile telecom industry for the efficiency assessment of the BTS. This work is unique because it focuses on a more technical side within non-technical factors and tries to provide technical insights to help optimization and planning engineers make the right decisions to save money for the mobile operators.

3.2 Research Goal

As cellular technology grows more extensive and sophisticated, the role of evaluation tools becomes more critical to continued long-term success in competitive businesses. It is important to provide an easy way for optimization engineers to assess the overall efficiency of the BTS and to determine the inefficient BTSs and the reference set for each. This will improve their efficiency and provide an actionable recommendation. Two main goals are targeted as significant outcomes from this research. The first one is identifying a way to simplify the BTS's assessment complexity. Particularly, establishing a model for the efficiency measurement that enables the RNO engineers to make the right decisions on the data since the cellular network settings are incredibly complex. The second goal is to improve the process of evaluating the BTS's productivity and efficiency based on multiple KPIs and to enhance the inefficient BTSs by using best practices. Aligning these goals will give a predicted outcome from this model and, matched with the practical field implementation by the RNO engineer, will help to define the limitations of the model. Tactical research goals are directly related and support the strategic goals of the cellular operators to enhance the cellular network infrastructure performance, and to satisfy the customers with quality services while surviving in a competitive market.

3.3 Research Questions

This research is organized to answer two critical questions. The first one is from a technical angle: What are the most critical factors that are used to evaluate the BTS efficiency? This suggests creating a new standard KPI that allows for assessing the BTSs' efficiency. The second question is: Which BTSs have the potential for better network performance as well as increasing profits? Identifying the areas of BTSs that could be considered effective in different areas will help the engineers and top management take initial actions to optimize the mobile network performance. These critical questions can lead to significant sub-questions in the future such as, can we increase the profit by focusing on the inefficient BTSs? With all of these questions, this research will be unique and will offer valuable contributions.

3.4 Research Objective

This research addresses how to improve the productivity and efficiency of mobile towers in developing countries. Furthermore, the primary objective of this research is to develop a decision model to enable better decision making within the BTS operation. By learning best practices from efficient BTSs and identifying the reference set, engineers can take the right actions to improve the configuration of the inefficient BTSs. The research purpose is to come up with a practical, robust, and multidimensional benchmarking model that helps engineers and managers make the right decisions. This model will also help decision-makers determine where they can invest in improving the BTSs, which leads to making critical decisions to enhance the coverage. In the case of using two different vendors, the model assesses whether or not the BTS efficiency has complied with the timeline to adopt common measurement KPIs and proposes the right measures, if appropriate, to enhance the network performance. Finally, this study hopes to develop a standard global mobile network KPI that indicates an ordinary BTS efficiency, which will allow vendors and operators to determine the BTS status.

Chapter 4 Methodology

The research can be done based on the distinction between qualitative data, quantitative data, or a mixture of both, and each one has several methods to analyze these data. In this research, quantitative methodologies are used since the quantitative analysis supports an in-depth understanding of the situation investigated. The methodologies including DEA, regression, and performance matrix are reviewed and discussed in detail and the stages as well as the way to connect them to get results.

4.1 Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is employed as the primary methodology to build the evaluating BTS model with multi-inputs and outputs. The DEA method was first proposed in 1978 (Chavula 2013), and it is used to determine the relative efficiency of a set of Decision-Making Units (DMU) and to evaluate the performance of these organizations. The relative efficiency of each DMU is defined in a nonlinear programming model. The DEA approach has been developed and applied in diversified scenarios from 1978 (Nayame *et al.* 2019), and there are many publications covering the bibliographies, qualitative, and quantitative aspects of the DEA method (Seiford 1997, Gattoufi *et al.* 2004, Cooper *et al.* 2006, Cook and Seiford 2009, Liu *et al.* 2013, Emrouznejad and Yang 2017). The DEA method can be used to comprehensively explain the structure of the production frontier, which helps to gain some insightful management information. In the early stage of DEA development with the first model of Charnes, Cooper, and Rhodes (Charnes *et al.* 1978), the DEA was only to measure technical efficiency, and the primary focus was on the relative efficiency of non-profit organizational units. After that, the method has been expanded to a wide range of models and applications.

4.1.1 DEA Model

The DEA method aims to find the DMUs that produce high output outcomes using low input resources. There are two main models, and the first model was developed by (Charnes *et al.* 1978) and known as a CCR model, which considers a constant return to scale (CRS). After the CCR approach was used, a new mathematical programming definition for efficiency was established by Banker using game theoretical models (Banker 1980). A study was concerned with evaluating the efficiency of a special education program to obtain boundaries or envelopes to ascertain the amount of resource conservation or output increasingly involved from refinements in the efficiency of the program and managerial role (Charnes *et al.* 1981). In this contribution, the uniqueness of the DEA approach from statistical approaches was explained, and the authors undertook another supplementary mathematical programming development to differentiate between management and program efficiency.

A new model, BCC, was developed that affects the efficient production surface and used the concept of variable returns to scale (VRS) (Banker 1984). With this model, some concepts were explicitly developed to examine specific characteristics of a production correspondence that allows the DEA to extend its application. Banker, Charnes, and Cooper had a new contribution together where they explained the new separate variable that helps to determine whether processes were conducted in regions of increasing, constant, or decreasing returns to scale (Banker *et al.* 1984). Figure 1.4 illustrates the basic concepts and approaches of DEA.

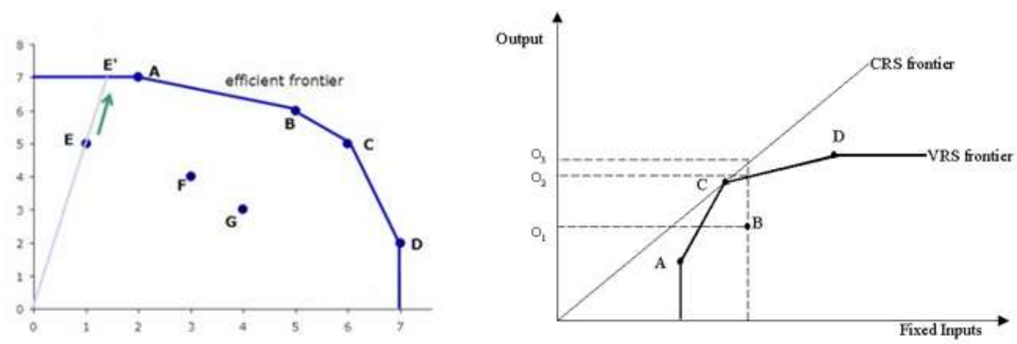


FIGURE 4.1: BASIC CONCEPTS OF DATA ENVELOPMENT ANALYSIS (DEA)

Other models have been developed including a non-oriented additive model (Charnes *et al.* 1985), Free Disposal Hull (FDH) nonconvex model (Tulkens 1993), and so on, but in this research, I will not adopt them. Furthermore, there are two approaches to implementing the DEA, which are minimizing the inputs "input-oriented" or maximizing the outputs "output-oriented." In this research, I use an output-oriented model with variable returns to scale (BCC-O model).

Andersen and Petersen proposed another approach to provide an efficiency rating of the efficient DMUs based on ignoring the very DMU under evaluationI – in other words, creating a frontier excluding itselffrom the possible reference set (Andersen and Petersen 1993). This approach was later dubbed super efficiency. It has been used todistinguish economically viable units from units that are only technically efficientand to rank the efficient DMUS.

4.1.2 DEA Formulas

Charnes, Cooper, and Rhodes explained the DEA as "a mathematical programming model applied to observational data that provides a new way of obtaining empirical estimates of extremal relations - such as the production functions and/or efficient production possibility surfaces that are a cornerstone of modern economics" (Charnes *et al.* 1978). The efficiency scores are measured in a bounded ratio scale by the fraction of the summation of weighted outputs to the summation of weighted inputs. In this research, the focus is on an output-oriented model with variable returns to scale (BCC-O model), and below is the mathematical expression for the BCC-O model of the envelopment model, in which DMU k can be thought of as to find a target constructed of a mix of the

DMUs described by a vector λ that uses no more input to achieve the same or more every output as DMU k:

$$\begin{aligned} \text{maximize} \quad & \phi \\ \text{subject to} \quad & \sum_{j=1}^{n} x_{i,j}\,\lambda_j \le x_{i,k} \forall\ i \\ & \sum_{j=1}^{n} y_{r,j}\,\lambda_j \ge \phi y_{r,k} \forall\ r \\ & \lambda_j \ge 0\ \forall\ j \end{aligned}$$

Below is another mathematical expression for the BCC-O model, which is simply the dual of the envelopment model:

$$\begin{aligned} \max \quad & \frac{\sum_{r=1}^{s} u_r\, y_{r,k}}{\sum_{i=1}^{s} v_i\, x_{i,k}} \\ \text{subject to} \quad & \frac{\sum_{r=1}^{s} u_r\, y_{r,k}}{\sum_{i=1}^{s} v_i\, x_{i,k}} = 1\ \forall\ j \\ & u_r, v_i \ge 0\ \forall\ r, i \end{aligned}$$

Assume that there are n DMUs that will be evaluated, (*DMUj: j = 1, 2,…, n*) and each DMU *j* has *m* inputs (x_i*: i = 1, 2, …, m*) to produce *s* outputs (y_r*: r = 1, 2,…,* *s*). The DEA aims to maximize the scalar measure of the efficiency of the DMU0. Also, this model can be transformed into the BCC-O multiplier model.

4.2 Performance Matrix

Several studies adopted the performance matrix approach and constructed it in different ways to outline the recommendations based on the four quadrants DMUs' position to improve overall efficiency and productivity. The efficiency matrix was proposed by (Dyson *et al.* 1990, Boussofiane *et al.* 1991), and it is a two-dimensional plot of the DMUs, and the principles of Boston Consulting group's product portfolio matrix (BCG matrix), which is explained in figure 4.2. The BCG matrix was introduced in the late 1960s as a growth-share matrix to help corporations to analyze their business units, and then in the late 1970s and early 1980s was widely known and used by companies to decide which markets and business units to invest (Hambrick *et al.* 1982, Morrison and Wensley 1991). Furthermore, the matrix approach was adopted for other purposes such as analyzing service operations, productive organization volume (Silvestro 1999), and service positioning strategies (Meirelles and Klement 2013).

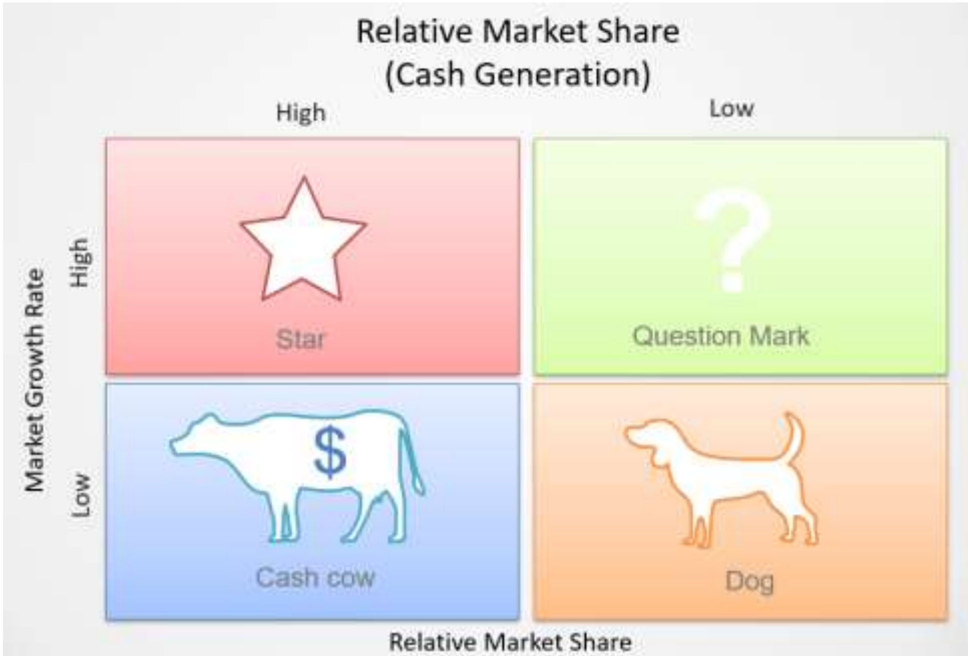


FIGURE 4.2: BOSTON CONSULTING GROUP'S (BCG) PRODUCT PORTFOLIO MATRIX

Several studies adopted the performance matrix approach and constructed it in different ways to outline the recommendations. The matrix has been heavily used to present the zones or relative positions for the banks (Camanho and Dyson 1999, Martins 2009, Lin and Chiu 2013, Moradi-Motlagh and Babacan 2015, Zimková and Others 2016) and to assess the efficiency of the railway (Lan and Lin 2006, Yu and Lin 2008, Doomernik 2015, Marchetti and Wanke 2017). In addition to the banking and transportation industries, the approach was adopted in the telecom industry to understand the impact of e-commerce in the semiconductor industry (Jantan *et al.* 2003).

Some of the studies built the matrix using two efficiencies. Lin and Chiu used two efficiencies, corporate and consumer service efficiency, to create the matrix and get further managerial insights into banking performance (Lin and Chiu 2013). Marchetti and Wanke plotted the efficiency scores in two dimensions using CRS model efficiency scores and the types of return to scales for each DMU to cluster the rail concessionaires that have similar characteristics in groups considering the value of the efficiency scores above or below mean (Marchetti and Wanke 2017). Moradi-Motlagh and Babacan used an efficiency matrix to present the zones or relative positions for the banks using pure technical efficiency and scale efficiency (Moradi-Motlagh and Babacan 2015). Martins used a two-stage model utilizing the matrix of intermediation efficiency vs. production efficiency and production efficiency vs. profitability to analyze the performance of the banking sector (Martins 2009). Yu and Lin decomposed the performance of the railways using the matrix of passenger vs. freight production efficiency (Yu and Lin 2008) and efficiency vs. effectiveness scores (Lan and Lin 2006) to improve their performance.

Alternately, other studies applied the performance matrix in different ways. Doomernik introduced the matrix to assess the efficiency of high-speed rail systems using production efficiency and service effectiveness (Doomernik 2015). Lo and Lu used the profitability and marketability efficiency matrix to discriminate between the financial holding companies for a small open economy (Lo and Lu

2006). In another study, the authors evaluated the impact of e-commerce on the roles of distributors using the matrix of technological and market maturity (Jantan *et al.* 2003).

Similar to my approach, other studies used efficiency and profitability to plot the matrix. Camanho and Dyson assessed bank branches using an efficiency-profitability matrix with technical efficiency and profit index, and they enabled the characterization of the branches' performance profile (Camanho and Dyson 1999). Thus, Johns, Howcroft, and Drake studied a hotel chain to provide a direct assessment of efficiency for the hospitality industry using efficiency vs. profitability matrix (Johns *et al.* 1997). In another study, the matrix was used as the efficiency-profitability managerial decision-making matrix, and the authors used technical efficiency scores together with the profitability indicators to analyze the bank branches visually (Zimková and Others 2016). My approach in this research is to adopt the performance matrix that includes the outcome technical efficiency score using the DEA model and the indicator of the profitability of DMU. This model will help managerial decision-makers assess the performance of the DMUs from different angles.

My approach allows for the combination of the technical and financial sides to provide a comprehensive picture of the DMUs' network performance. The matrix has four quadrants where each axis is divided into two levels. Zone 1 represents the DMUs that rate poorly in both efficiency and profit. Zone 2 represents the DMUs that rank poorly in the efficiency, but high in profit. Zone 3 represents the DMUs that have a high rate of efficiency but rate poorly in profit. Zone 4 represents the DMUs that have a high rate of both efficiency and profit. Figure 4.3 explains the proposed matrix.

The literature highlighted many advantages of integrating the performance matrix approach, and it will help to provide alternative target setting strategies (Camanho and Dyson 1999) adopted for applicable policies for different situations (Lan and Lin 2006, Yu and Lin 2008). The performance matrix approach created a strategic positioning of the service system (Meirelles and Klement 2013). Additionally, Moradi-Motlagh and Babacan pointed out the advantage of analyzing the DMUs using visual tools where decision-makers and managers can uncover opportunities for improvement while making the right actions and monitoring for each category of DMUs (Moradi-Motlagh and Babacan 2015). Doomernik mentioned that by plotting the efficiency and effectiveness of DMU's in a performance matrix, strategies could be found to improve the position of underperformers (Doomernik 2015). Lin and Chiu proposed this approach to enhance operational performance (Lin and Chiu 2013). They found by decomposing the performance into four-dimensional tactic, firms and organizations can evaluate the branches' performance and priority the managerial implications.

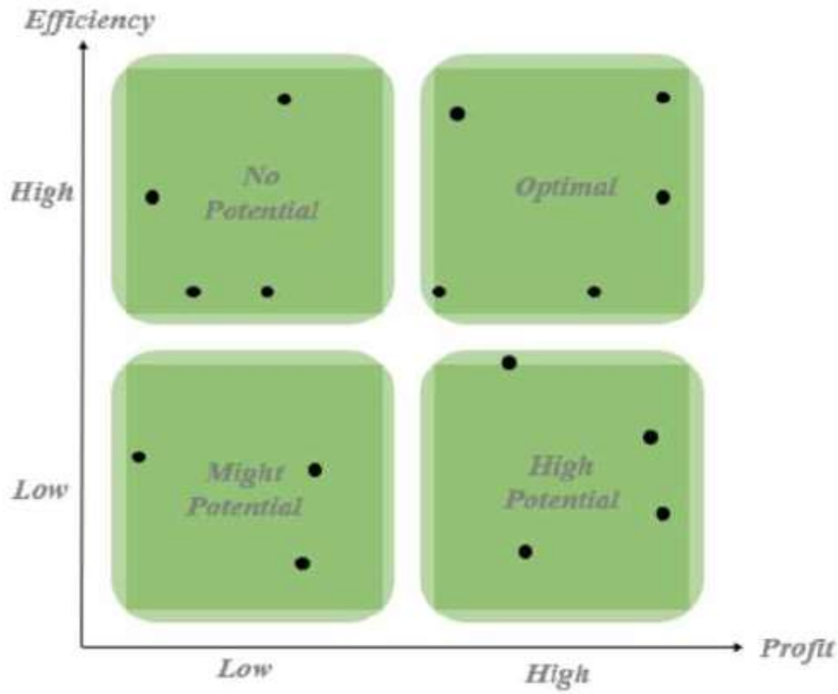


FIGURE 4.3: GENERAL PERFORMANCE MATRIX IN THIS RESEARCH

4.3 Statistical Analysis and Regression Analysis

Thus, from the previous deep literature and analysis, DEA and data mining individually cannot give enough details of factors related to inefficient DMUs (Emrouznejad and Anouze 2010). In order to bring about clear and concrete managerial insights to improve the performances of DMUs, the DEA's results should have another step of interpretation for the transformation such as the relationships between inputs and outputs using statistical analysis. Moreover, integrating different methodologies affords a more significant opportunity for the user to get more meaningful results. Therefore, this level can be achieved by integrating some of the statistical analyses.

The primary objective of data mining techniques is to build a useful predictive or descriptive model using extensive data (Chen *et al.* 2015). It has been developed over time to answer questions starting from the basic one of just information about data to cover the question of the data trend. Additionally, data mining can be used to find patterns and connections as well as to learn more about customers and make smart marketing decisions (Bharati 2010). In the context of data mining definition, the regression analysis will be used in this research. The regression analysis is a powerful statistical tool, which aims to explain how and to what extent variables are associated with each other. Regression is one of the more widely used methods in data analysis, and there are various kinds of regression techniques available including simple linear regression, multiple regression, logistic regression, polynomial regression, stepwise regression, and so on. Additionally, regression analysis is the most widely used in all statistical techniques, and it has been applied in many applications and technical problems (Izenman 2008). One of the values of constructing relationships and correlation using regression analysis is that the validation using various tests can be employed to determine if the results are satisfactory.

Using statistical analysis is beneficial in terms of indicating the significant relationships between the dependent variable and the independent variable, which helps to signify the strength of the impact of multiple independent variables on the dependent variable. As regarded in this research objective, the regression analysis will be carried out in two main stages including discovering the relationship between the DEA efficiency and independent variables, namely KPIs, and processing logic of the BTS setting changes. In other words, based on the DEA efficiency results, the traditional regression analysis will be applied in two stages:

- The first one is to explore the impact of the variables in terms of inputs and outputs on the DEA efficacy. This will help us to clarify the driver KPIs in the model.

- The second stage is to process data and determine the effectiveness of the BTS's tuning parameters and setting based on its efficacy. The BTS's structure can be divided into three essential groups including hardware, software, and external factors.

4.4 Using R Environment

Using computer software has become essential to perform the analysis of the DEA since data has grown more substantial, and the applications evolve into greater complexity. This dependence on software was employed to ensure accurate results. Moreover, to do the DEA analysis, researchers need to do the calculations. Therefore, each researcher used software or tools that make this analysis easy regarding time and accuracy. Since the early 1980s, the computer codes and tools were available for such DEA studies (Charnes *et al.* 1984).

In this research, the language R is adopted as statistical computing to do the calculation of the efficiency since it is widely used among statisticians and data miners for data analysis. The main DEA packages that will be used to get the result are DJL, written by Dong-Joon Lim, Ph.D., and MultiplierDEA, written by Aurobindh Kalathil Puthanpura. Appendix A shows the initial R code that will be used in this research analysis to get the efficiency results. Also, RMarkdwon has been used for writing the dissertation and creating a defense presentation.

Chapter 5 Research Design

The flow chart in figure 5.1 illustrates the research map, which is divided into four stages. The first stage is the literature review including three main categories: application, methodological, and domain. The second stage is preparing the model for analysis. The third stage is completing the analysis and obtaining the results. The results will be divided into three phases: DEA efficiency analysis, the performance matrix analysis, and regression analysis. The last stage is validating the research and defining the research contribution.

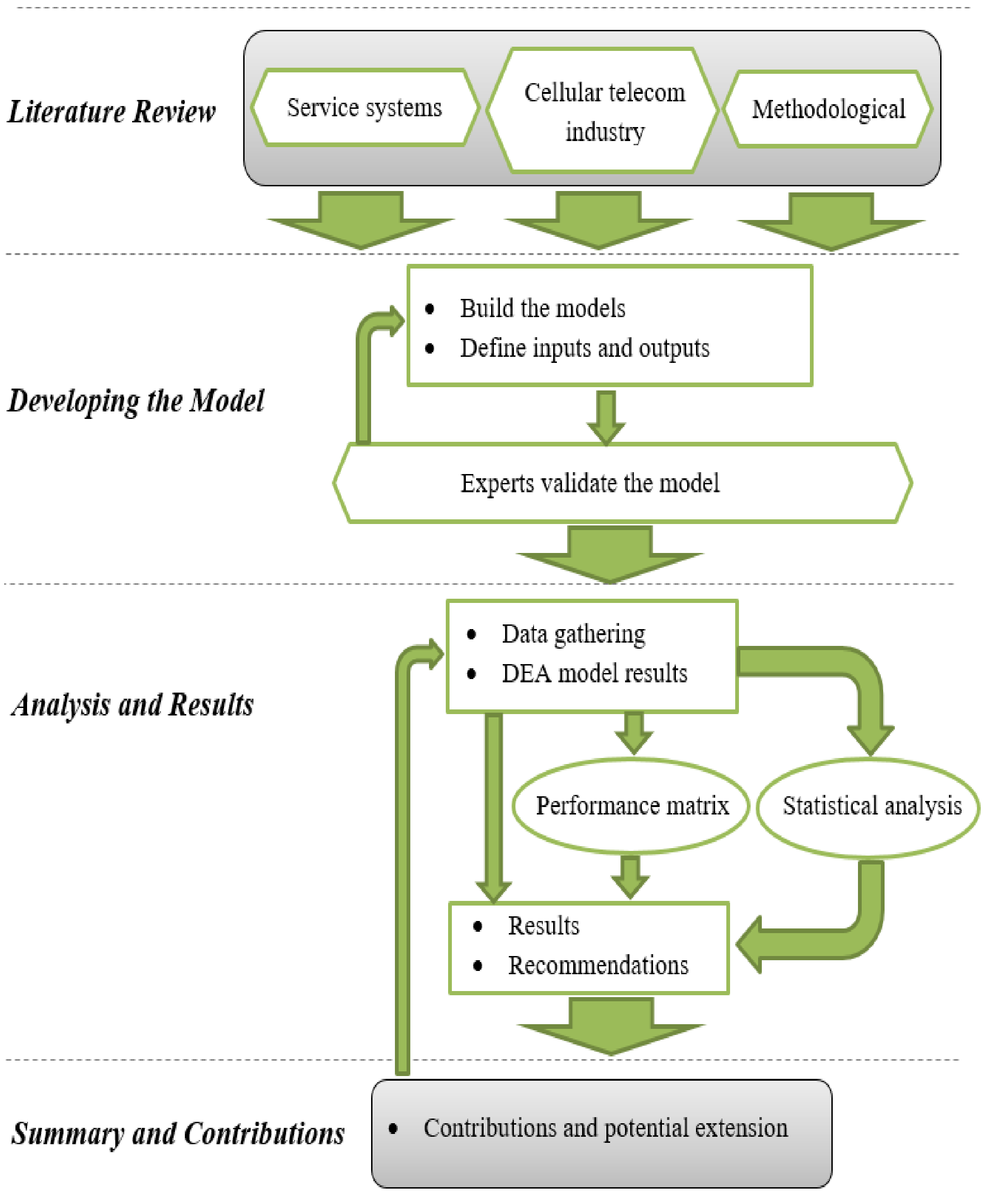


FIGURE 5.1: THE RESEARCH FRAMEWORK MAP

5.1 The Research Models

5.1.1 Data Gathering

This research relies on measurements from a local mobile operator in Libya and obtains real network data. Almadar Aljadid is one of two mobile operators in Libya. Founded in 1995, it was known by the name of Al Madar Telecom Company. It was launched as a pilot network in Tripoli in 1996. The service launched commercially in 1997 (Almadar Aljadid). In this research, I will focus on the Great Tripoli Polygon area, which includes around 300 mobile towers. Figure 5.2 display the area and the base stations that will be considered in this research.

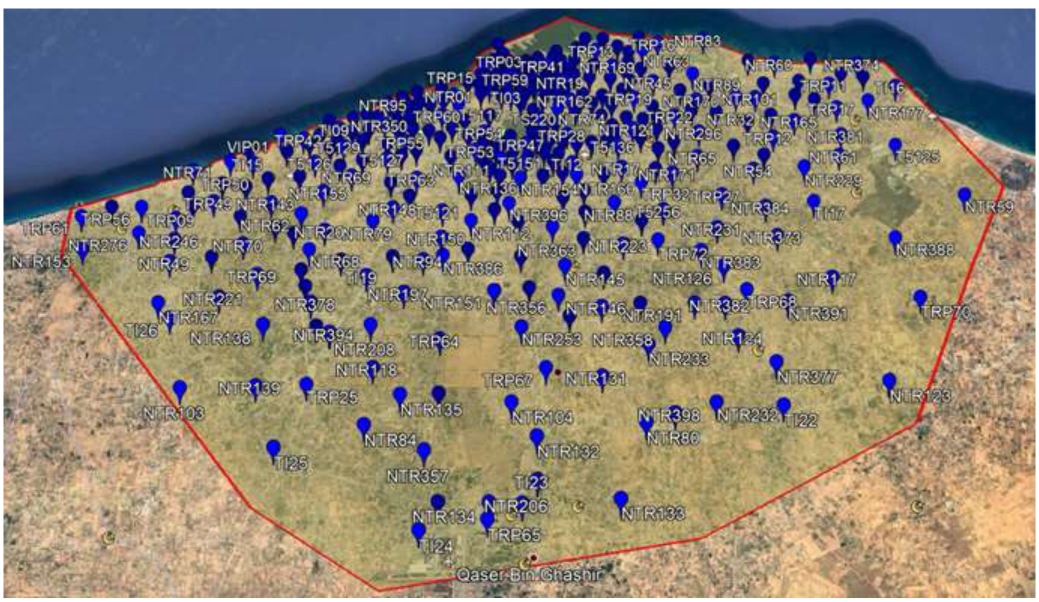


FIGURE 5.2: THE GREAT TRIPOLI POLYGON AREA

5.1.2 Building the Models

One of the most critical components in the research is building the appropriate model. From my experience as an engineer and technical manager in the optimization and planning department at Almadar Aljadid Co., the models with the most relevant KPIs were selected. Figure 5.3 illustrates the five models with inputs and outputs. These models were built based on the most critical service quality indicators of accessibility, retainability, mobility, and service integrity KPIs, which represent each service quality group. The next section explains the inputs and outputs that will be used in the initial models, where I expect to get significant insights.

Inputs KPIs		*Outputs KPIs*	
R 1	TCH Time slots	**KPI 3**	Traffic (Erlang)
		KPI 4	SDCCH Traffic (Erlang)
		KPI 5	Random Access Success
		KPI 6	TCH Success
R 2	SDCCH Time slots	**KPI 7**	SDCCH Success
		KPI 8	Handover Success
		KPI 9	Speech Good Quality

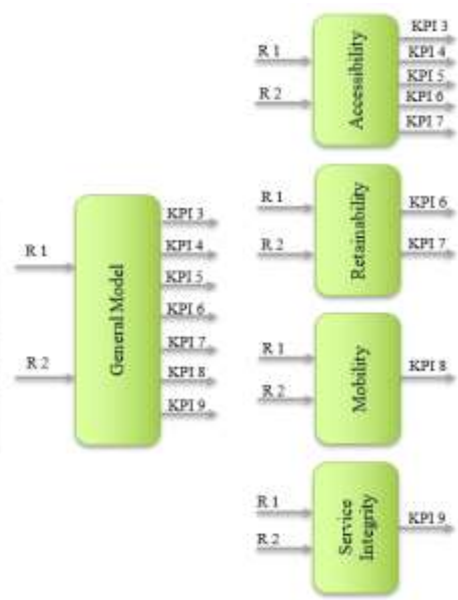


FIGURE 5.3: THE INITIAL DEA MODELS WITH INPUTS AND OUTPUTS

5.1.2.1 Input and Output Variables

One of the essential components of building a practical model of DEA is selecting relevant inputs and outputs. This study is based only on the technical data of the considered mobile base stations. The process of the voice call to the mobile subscriber starts with RACH to request a signaling channel. Then, the MS sends a call setup request using SDCCH, and then the BSC allocates an idle TCH. During this process, the BTS and MS are told to tune to the TCH, and then a connection is established. These main processes have essential KPIs that represent the level of quality as seen by the subscriber. Therefore, we focus on the most relevant performance KPIs as outputs and the cell resources as inputs.

- **Input**
  - **The number of TCH time slots:** the number of time slots in the physical units, TRU, that specify the capacity of the cell. Depending on the configuration, each TRU can serve between eight and sixteen users simultaneously.
  - **The number of SDCCH time slots:** the number of time slots in the physical units, TRU, that specify the capacity of the signaling. Depending on the configuration, each TRU can serve between sixty-four and one hundred twenty-eight users simultaneously.

- **Outputs**

  - **TCH Traffic (Erlang):** used to measure the traffic density for the TCH channel during a time window where one Erlang is equal to one hour of traffic. A TCH channel is used to carry voice or data traffic.
  - **SDCCH Traffic (Erlang):** used to measure the traffic density for the SDCCH channel during a time window where one Erlang is equal to one hour of traffic. SDCCH traffic is used to carry short message traffic or for network signaling.
  - **TCH Success:** the number of successful TCH assignment to all subscribers on the cell.
  - **SDCCH Success:** the number of successful SDCCH assignment to all subscribers on the cell.
  - **Random Access Success:** the number of successful attempts by all of the subscribers on the cell when randomly attempting to get an SDCCH channel.
  - **Handover Success:** the number of successful times when the subscriber "who has TCH or SDCCH resource" moved from one cell to another cell.

– **Speech Good Quality:** the quality of the speech during the call experienced by the end-user.

5.2 Procedures of the Analysis

After determining the efficiency score for each BTS, the super-efficiency was found to differentiate between the efficient BTSs. Additionally, the amounts and total weights of these BTSs that are counted in the reference set will be listed. This list explains the best practices in terms of the significance of each BTS concerning other inefficient BTS. As a second stage, the secondary methods, regression analysis, and performance matrix will be integrated to get more insights. After these analyses, recommendations to make the setting changes for the inefficient BTSs will be given to the optimization engineers. Some studies have addressed the influences of external environmental factors on the production process where the producer does not have the control of some inputs and/or outputs (Banker 1986; Daraio and Simar 2005; Guo 2009). However, this model focuses on BTS resources as inputs and the BTS's KPIs that are related to measuring the efficiency as outputs. Also, the BTS's parameters, which are controllable and changeable, will be used as a tuning based on best practices. Factors such as system model upgrade, usage of frequency bands, changes in the BTS's offset, and so on, can be copied or reproduced from the efficient BTS that follows on the inefficient BTS reference set. In the case of using controllable inputs in the model, the high performance becomes a function of management decisions, which in turn leads to identifying best practices.

5.3 Validation Process

One study (Beecham *et al.* 2005) summarized the validation process as determining the objectives of building the model, preparing the criteria of development, identifying the alternative methods, designing a validation method, selecting the expert panel, presenting results, connecting results with the success criteria, and finding the impact and the changes. In this research, the validation process is divided into three steps. The first stage is preparation including the selection of the expert. For this step, I consult with the region expert leaders. Then I finalize the list of the experts who later I contact to introduce my research problem, objective, and goal. The second stage is the validation of the model, so I send the initial model and get feedback from the experts and make any changes to the model. Before the final stage, I update the list of the experts based on the level of contribution and add additional experts if needed. In the future work, it is nice to implement the last stage, which includes validating the results and incorporating the recommendations from my analysis, check for feedback, and determine if there are more changes. Figure 5.4 explains the process in a flowchart.

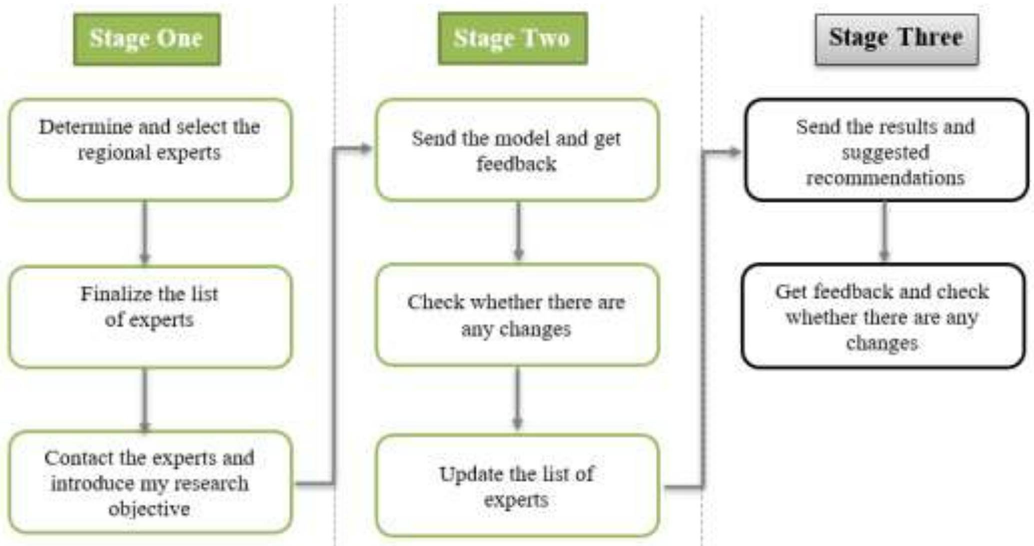


FIGURE 5.4: THE EXPERTS' VALIDATION PROCESS

Chapter 6 Research Analysis and Case Study

6.1 Libyan Mobile Telecom Industry

With all the changes and challenges in the Libyan situation, the country possesses many positive attributes for carefully targeted investment in several sectors. It seeks to use the latest updated technology to improve the public service. However, due to rapid and discontinuous changes in telecom technology, market demand, future-focused enterprises, and Libyan circumstances, the Libyan Ministry of Telecommunication needs to increase the organizational responsiveness of the telecom sector through the redesign and development of the existing companies and the implementation of innovative strategies and processes. Therefore, there are many alternatives including adapting, integrating, and re-configuring the cellular telecom infrastructures. Libya has two local operators, Almadar Aljadid and Libyana Mobile Phone Companies, which are managed by the Libyan Post Telecommunications and Information Technology Company (LPTIC) under the Libyan Ministry of telecommunication. The LPTIC was established in 2005 as a holding company for the owner of major communications companies in Libya ("LPTIC overview, website" n.d.). The purpose of creating LPTIC was to invest in the telecommunications infrastructure in the country and abroad, and to support the development of the new Libya telecom and information technology services-based economy, and to meet customer satisfaction.

Almadar Aljadid was established in 1995 as the first mobile operator in Libya and North Africa, and it has over three million subscribers including government establishments, businesses, and individuals. It is well known for its high-quality services (Aljadid n.d.). On the other hand, Libyana started its first mobile services in September 2004 and quickly achieved success in the market with more than 6.2 million subscribers during the first four years, which is about 116% of the Libyan population ("Libyana...The biggest mobile operator in Libya" n.d.). Thus, Libya recently tried the phenomenon of the Mobile Virtual Network Operator, where the two providers, Libyan and Almadar, leased their network and sold minutes of communication to the third-party providers. However, while these third-party companies were under the same Libyan Ministry of Telecommunication that monitors telecom services, LTT and Aljeal Aljadid, they did not have their own networks.

This experiment was not successful. Although the Ministry and its national operators sought to catch up with the fast growth of the technology and to provide the best service to the customers, the sector needs some reforms. As a result, the Libyan Ministry of Telecommunication is interested in long-term investment in the cellular telecom industry to enhance the mobile telecom sector. A study using the Hierarchical Decision Model (HDM) based on Libyan experts' judgments in the telecom sector found that licensing a new foreign operator is considered the best option in the case of Libya (Dabab *et al.* 2019). In doing so, the local providers should prepare for the coming situation.

6.2 Data and Efficiency Measurement

This research relies on measurements from a local mobile operator in Libya, and obtains real network data of Almadar Aljadid, which is one of two mobile operators in Libya founded in 1995. It was known by the name of Al Madar Telecom Company and launched as a pilot network in Tripoli in 1996. The service launched commercially in 1997 (Aljadid n.d.). In this research, I will focus on the Great Tripoli Polygon area, which includes 434 mobile towers. Figure 5.2 displays the area and the base stations that will be considered in this research. Table 6.1 shows the first six rows of the data used to build the models, and Table 6.2 shows the data used for parameter tuning to set the recommendations. Due to data confidentiality, I re-scaled and coded the data to lose its sensitivity, but the results of DEA were not affected, and I still have the same results. Table 6.3 illustrates the statistical summary of the first group of the data to give an overview of the data.

TABLE 6.1: SAMPLE DATA OF THE BTS OF BUILDING THE MODELS

Index	TCH_NO	SDCCH_NO	TCH_T	SDCCH_T	TCH_SUCC	SDCCH_SUC	RACH_SUC	HO_SUC	SQI_G	Revenue
BTS_1	168	36	23.73	4.368	231	352	283	118	1022	21
BTS_2	168	36	20.23	24.1	204	538	836	59	655	18
BTS_3	108	24	37.32	23.22	492	1848	1568	382	1165	31
BTS_4	168	44	16.98	20.36	187	428	700	34	426	3
BTS_5	136	36	46.23	7.748	434	632	500	237	1815	0
BTS_6	152	32	64.14	13.21	736	901	738	316	2430	62

TABLE 6.2: SAMPLE DATA OF THE BTS OF TUNING THE PARAMETERS

Index	No. Frequencies	No. Neighbors	Site Category	RBS Type	Technology	Antenna Type	Antenna Tilt	Height	DTHAMR	DTHNAMR
BTS_1	40	20	1	1	1	1	0	55	45	15
BTS_2	26	15	1	1	1	1	0	30	100	100
BTS_3	36	20	1	1	1	2	0	28	70	68
BTS_4	18	9	1	1	1	1	2	50	100	100
BTS_5	20	10	1	1	1	1	2	42	100	100
BTS_6	26	13	1	1	1	2	4	40	100	100

TABLE 6.3: BASIC DESCRIPTIVE STATISTICS OF THE DATA

	TCH_NO	**SDCCH_NO**	**TCH_T**	**SDCCH_T**	**TCH_SUCC**	**SDCCH_SUC**	**RACH_SUC**	**HO_SUC**	**SQI_G**	**Revenue**
Median	168	36	70.12	19.12	738	1381	1213	1210	2345	286.5
Mean	184.4	35.28	77.99	23.18	880.4	1670	1552	1316	2548	281.2
Var	3955	34.87	1210	274.4	220412	1164318	1650253	352308	1202408	21396
S.D	62.89	5.905	34.78	16.57	469.5	1079	1285	593.6	1097	146.3

I divided my analysis into four models, and I analyze each model.

6.2.1 General Model (GM)

As I mentioned before, the general model contains all of the inputs and outputs, and Figure 6.1 illustrates the model in more detail.

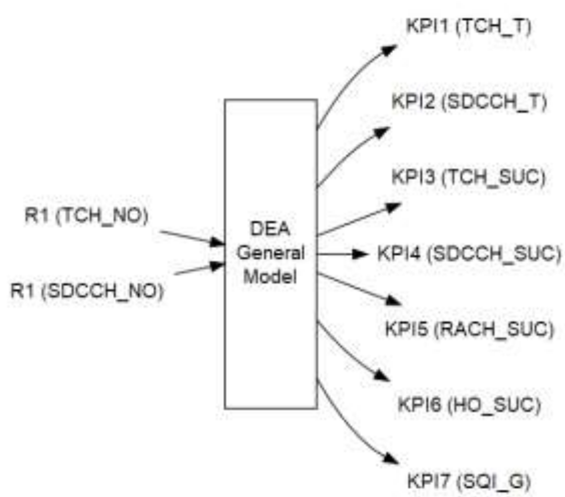


FIGURE 6.1: GENERAL MODEL DIAGRAM

After I applied the DEA method using the right package, I got the results of the efficiency and super efficiency for all Decision-Making Units (DMU). Table 6.4 shows a sample of the results. The rest of the results are provided in Appendix B. In this model, there are 434 DMUs that are efficient, and efficiency distribution scores are displayed in Figure 6.2 on the scale.

TABLE 6.4: VRS-OUTPUT EFFICIENCY SAMPLE RESULTS

Index	BTS Efficiency GM
BTS_1	0.159
BTS_2	0.2184
BTS_3	0.5104
BTS_4	0.1845
BTS_5	0.3548
BTS_6	0.421

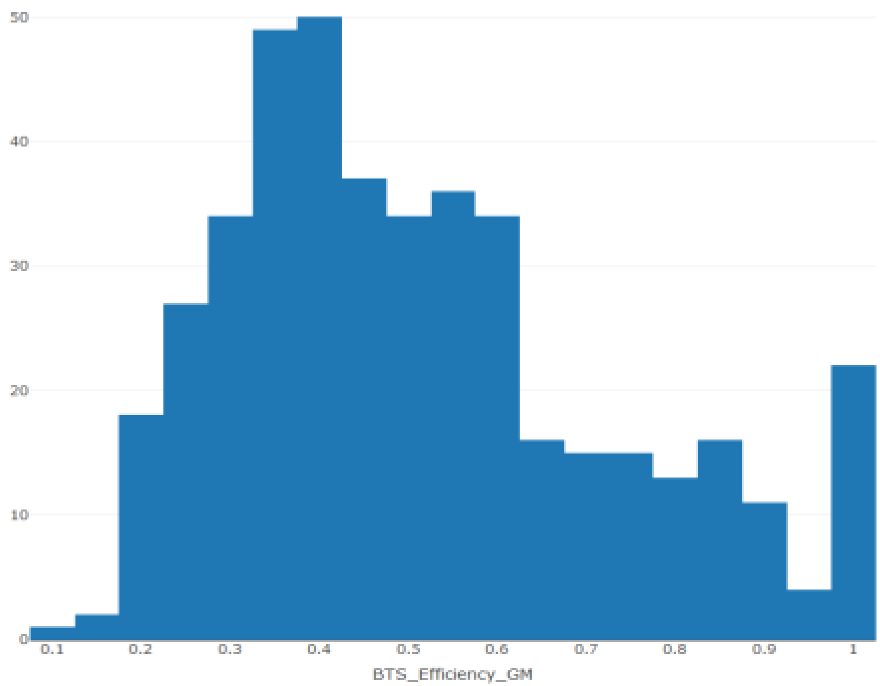


FIGURE 6.2: HISTOGRAM OF EFFICIENCY RESULTS DISTRIBUTION OF THE GM

In order to differentiate between the efficient BTS, super-efficiency was calculated. Table 6.5 shows the highest super efficiency, and Figure 6.3 displays super-efficiency distribution scores of all BTSs on the scale.

Table 6.5 BTS'S SUPER EFFICIENCY SAMPLE RESULTS

BTS Super Efficiency GM
1.67
1.594
1.451
1.309
1.266
1.261

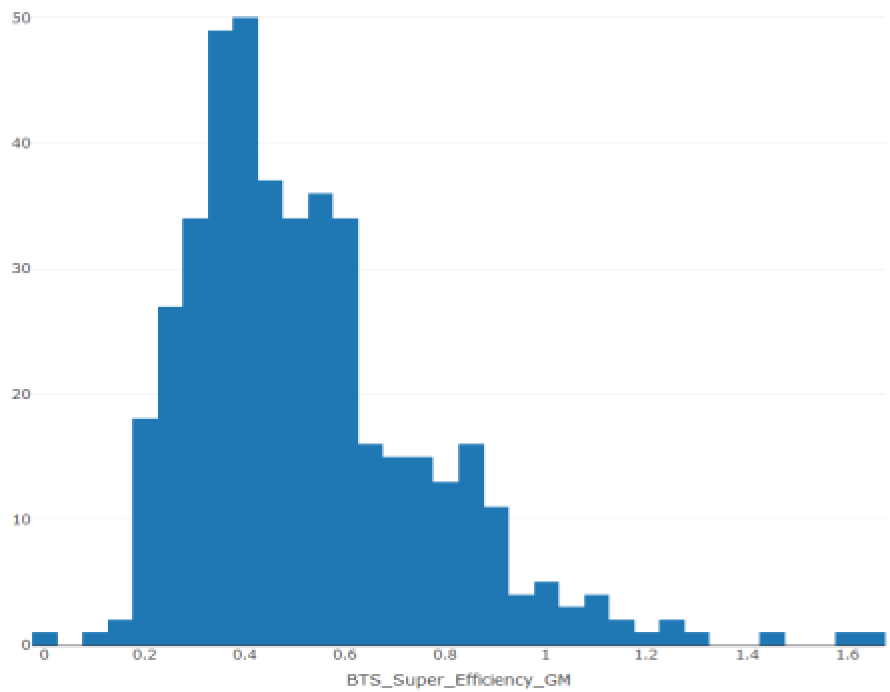


FIGURE 6.3: HISTOGRAM OF SUPER EFFICIENCY RESULTS DISTRIBUTION OF THE GM

After I got the efficiency of each BTS, I plotted all of the DMUs on the performance matrix using the efficiency score and revenue in that hour. The thresholds on the horizontal axis, x-axis, which performs as the revenue threshold was taken as a rough number. The thresholds in the vertical axis, y-axis, which conducts the efficiency score is considered in 70%. Figure 6.4 shows the graph, and I used different colors to define the different efficiency groups, and I used different sizes to describe the different profitability groups. As a result, I got four different groups including:

- The optimal group that has high efficiency and high profit.
- High opportunity group that has high profit and low efficiency.
- Medium opportunity group that has low profit and low efficiency.
- And low opportunity group that has low profit and high efficiency.

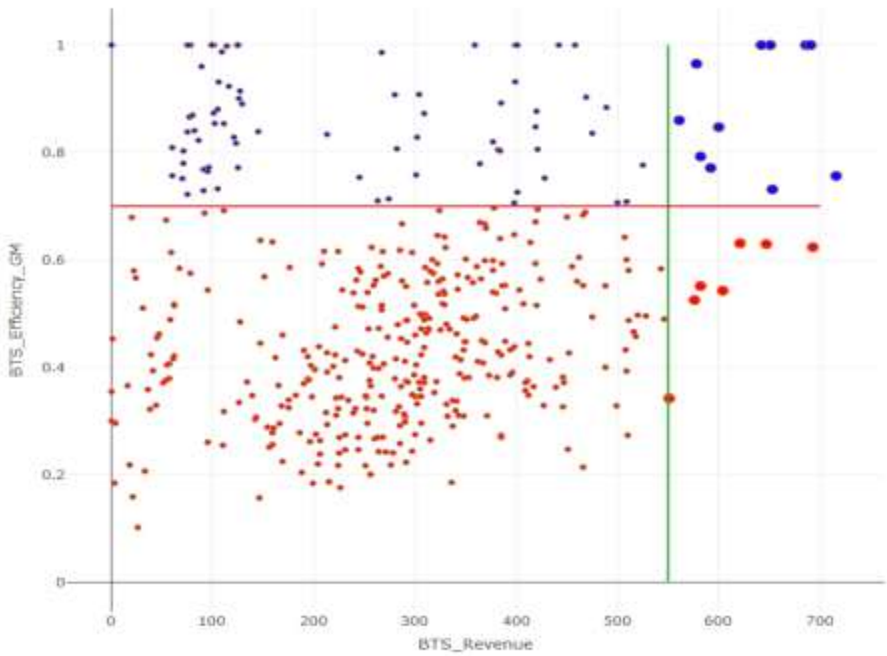


FIGURE 6.4: PERFORMANCE MATRIX TO SHOW THE FOUR CATEGORIES OF THE GM

Tables 6.6, 6.7, 6.8, and 6.9 display six rows of the results of each group respectively. The tables include the names of BTSs, efficiency score, super efficiency score, and the revenue. See the Appendix C for all results of the high opportunity group.

TABLE 6.6: CATEGORY 1 OF GENERAL MODEL (OPTIMAL BTSS)

BTS	BTS Efficiency GM	BTS Super Efficiency GM	BTS Revenue
BTS_32	1	1.127	686
BTS_38	1	1.107	691
BTS_47	0.7563	0.7563	716
BTS_101	0.8473	0.8473	600
BTS_132	1	1.052	651
BTS_191	0.9652	0.9652	578

TABLE 6.7: CATEGORY 2 OF GENERAL MODEL (HIGH OPPORTUNITY BTSS)

BTS	BTS Efficiency GM	BTS Super Efficiency GM	BTS Revenue
BTS_19	0.6293	0.6293	647
BTS_71	0.6308	0.6308	621
BTS_75	0.5515	0.5515	582
BTS_76	0.5253	0.5253	576
BTS_77	0.6237	0.6237	693
BTS_105	0.3422	0.3422	551

TABLE 6.8: CATEGORY 3 OF GENERAL MODEL (MEDIUM OPPORTUNITY BTSS)

BTS	BTS Efficiency GM	BTS Super Efficiency GM	BTS Revenue
BTS_1	0.159	0.159	21
BTS_2	0.2184	0.2184	18
BTS_3	0.5104	0.5104	31
BTS_4	0.1845	0.1845	3
BTS_5	0.3548	0.3548	0
BTS_6	0.421	0.421	62

TABLE 6.9: CATEGORY 4 OF GENERAL MODEL (LOW OPPORTUNITY BTSS)

BTS	BTS Efficiency GM	BTS Super Efficiency GM	BTS Revenue
BTS_7	0.7717	0.7717	125
BTS_8	0.8538	0.8538	111
BTS_9	0.9005	0.9005	126
BTS_10	1	1.005	101
BTS_12	0.8092	0.8092	60
BTS_15	0.7567	0.7567	60

In this research, I focused on one group, which is the high opportunity group. In Figure 6.4, the scatter plot displays this group as large red data points. Table 6.10 has all of them with efficiency and profit scores as well as the reference set of each one. In this model, we have ten branches that have a high opportunity, and that have more priorities for top management to do to enhance efficiency.

TABLE 6.10: SAMPLE OF FINAL RESULTS OF CATEGORY 2 FOR GENERAL MODEL WITH THE REFERENCE SET

BTS	BTS Efficiency GM	BTS Revenue	BTS_38	BTS_222	BTS_282	BTS_286	BTS_304	BTS_313
BTS_105	0.3422	551	0	0.007	0	0.1759	0.5131	0.3031
BTS_138	0.5427	604	0	0.00007	0	0.5017	0.3818	0.1163
BTS_19	0.6293	647	0	0	0	0	0.3489	0.6510
BTS_71	0.6308	621	0.1675	0.0014	0.0321	0	0	0.7988
BTS_75	0.5515	582	0	0.0052	0	0.1176	0.4113	0.4657
BTS_76	0.5253	576	0	0	0	0	0.3711	0.6288
BTS_77	0.6237	693	0	0.0066	0	0.1496	0.1288	0.7147

6.2.2 Accessibility Model (AM)

The same steps that were taken in the general model are also followed in this model. The inputs and outputs of the model are illustrated in Figure 6.5. Table 6.11 shows a sample of efficiency and super-efficiency, in which eight branches are efficient. Additionally, Tables 6.11-6.18 and Figures 6.6-6.8 display the results of this model.

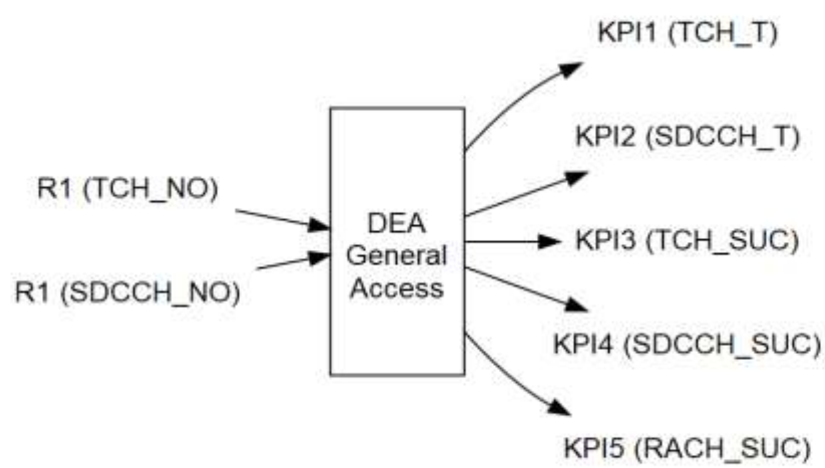


FIGURE 6.5: ACCESSIBILITY MODEL DIAGRAM

TABLE 6.11: VRS-OUTPUT EFFICIENCY SAMPLE RESULTS

Index	BTS Efficiency AM
BTS_1	0.115
BTS_2	0.2184
BTS_3	0.5104
BTS_4	0.1845
BTS_5	0.2871
BTS_6	0.3489

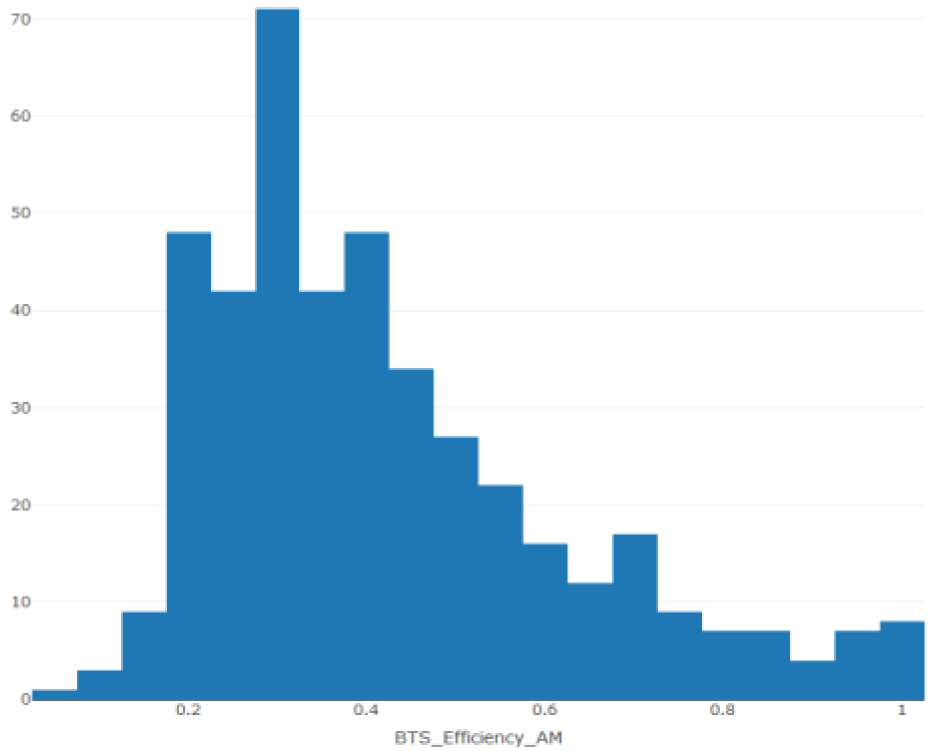


FIGURE 6.6: HISTOGRAM OF EFFICIENCY RESULTS DISTRIBUTION OF THE AM

TABLE 6.12: BTS'S SUPER EFFICIENCY SAMPLE RESULTS

BTS Super Efficiency AM
1.67
1.455
1.229
1.194
1.182
1.158

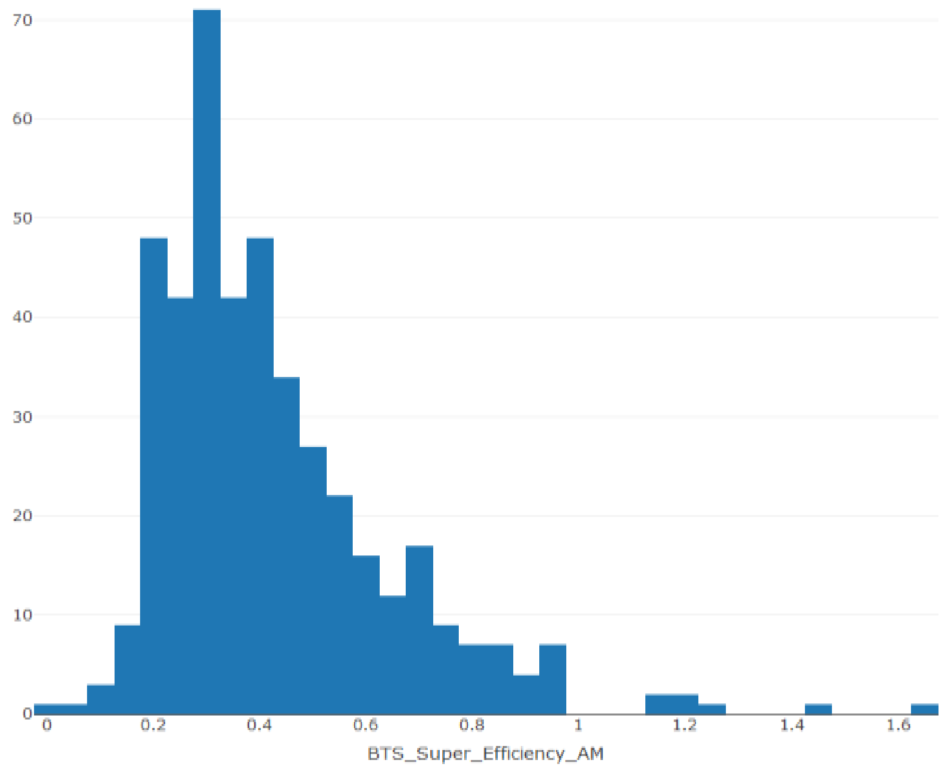


FIGURE 6.7: HISTOGRAM OF SUPER EFFICIENCY RESULTS DISTRIBUTION OF THE AM

TABLE 6.13: BTS'S EFFICIENCY SAMPLE RESULTS

BTS	BTS Efficiency AM	BTS Super Efficiency AM
BTS_36	1	1.156
BTS_222	1	1.455
BTS_282	1	1.229
BTS_284	1	1.158
BTS_285	1	1.67
BTS_286	1	1.194

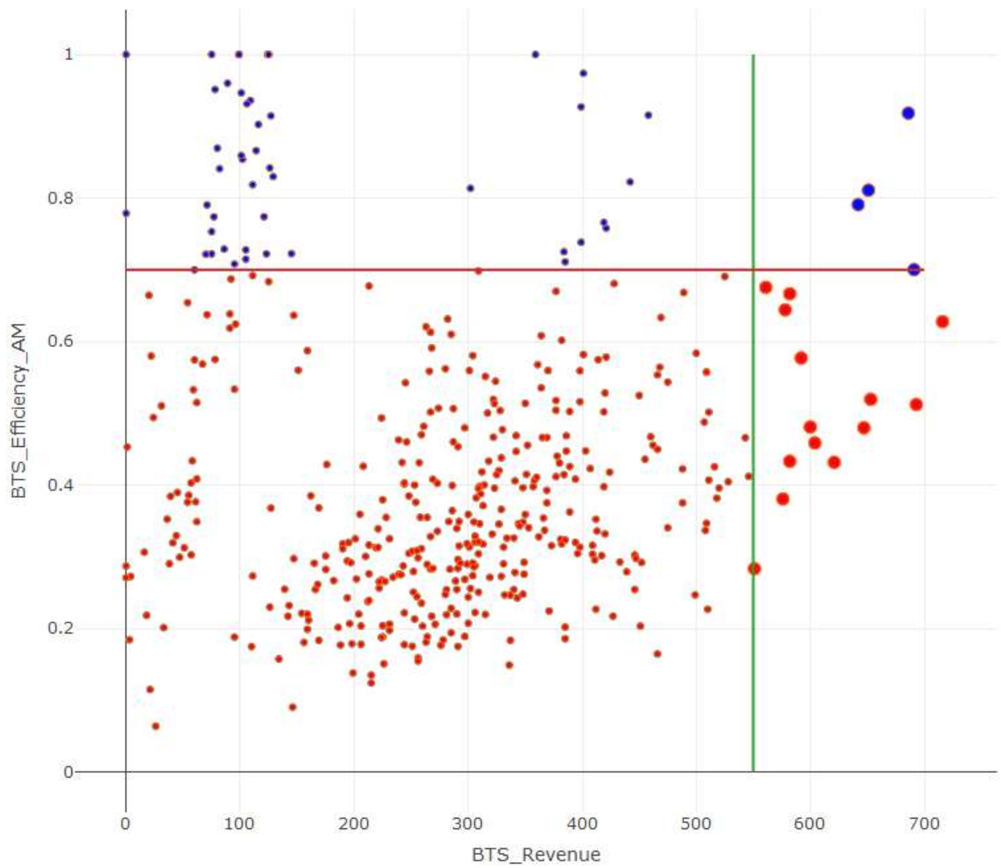


FIGURE 6.8: PERFORMANCE MATRIX TO SHOW THE FOUR CATEGORIES OF THE AM

TABLE 6.14: CATEGORY 1 OF ACCESS MODEL (OPTIMAL BTSS)

BTS	BTS Efficiency AM	BTS Super Efficiency AM	BTS Revenue
BTS_32	0.9182	0.9182	686
BTS_38	0.7001	0.7001	691
BTS_132	0.8109	0.8109	651
BTS_304	0.7908	0.7908	642

TABLE 6.15: CATEGORY 2 OF ACCESS MODEL (HIGH OPPORTUNITY BTSS)

BTS	BTS Efficiency AM	BTS Super Efficiency AM	BTS Revenue
BTS_19	0.4798	0.4798	647
BTS_47	0.6278	0.6278	716
BTS_71	0.4317	0.4317	621
BTS_75	0.4331	0.4331	582
BTS_76	0.3807	0.3807	576
BTS_77	0.5122	0.5122	693

TABLE 6.16: CATEGORY 3 OF ACCESS MODEL (MEDIUM OPPORTUNITY BTSS)

BTS	BTS Efficiency AM	BTS Super Efficiency AM	BTS Revenue
BTS_1	0.115	0.115	21
BTS_2	0.2184	0.2184	18
BTS_3	0.5104	0.5104	31
BTS_4	0.1845	0.1845	3
BTS_5	0.2871	0.2871	0
BTS_6	0.3489	0.3489	62

TABLE 6.17: CATEGORY 4 OF ACCESS MODEL (LOW OPPORTUNITY BTSS)

BTS	BTS Efficiency AM	BTS Super Efficiency AM	BTS Revenue
BTS_8	0.8186	0.8186	111
BTS_9	0.8419	0.8419	126
BTS_10	0.9465	0.9465	101
BTS_12	0.7	0.7	60
BTS_35	0.8408	0.8408	82
BTS_36	1	1.156	124

TABLE 6.18: SAMPLE OF FINAL RESULTS OF CATEGORY 2 FOR ACCESS MODEL WITH THE REFERENCE SET

BTS	BTS Efficiency AM	BTS Revenue	BTS_222	BTS_285	BTS_286
BTS_101	0.4809	600	0.0425	0	0.9574
BTS_105	0.2834	551	0	0.1538	0.8461
BTS_138	0.4587	604	0.0212	0	0.9787
BTS_19	0.4798	647	0	0.1538	0.8461
BTS_191	0.6442	578	0.0425	0	0.9574
BTS_227	0.5195	653	0.0170	0.0920	0.8908

6.2.3 Retainability Model (RM)

The same steps that were taken in the general model and Model 1 are also followed in this model. The inputs and outputs of the model are illustrated in Figure 6.9. Table 6.19 shows a sample of efficiency and super-efficiency, in which eighteen branches are efficient. Additionally, Tables 6.19-6.26 and Figures 6.10-6.13 display the results of this model.

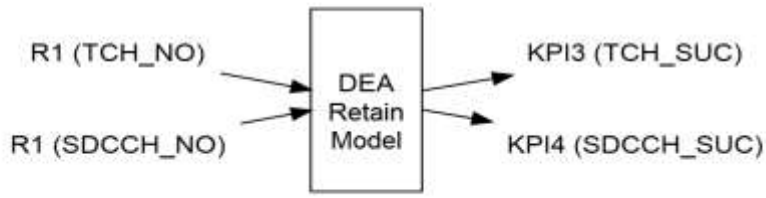


FIGURE 6.9: RETAINABILITY MODEL DIAGRAM

TABLE 6.19: VRS-OUTPUT EFFICIENCY SAMPLE RESULTS

Index	BTS Efficiency RM
BTS_1	0.09576
BTS_2	0.08637
BTS_3	0.5104
BTS_4	0.07752
BTS_5	0.232
BTS_6	0.3437

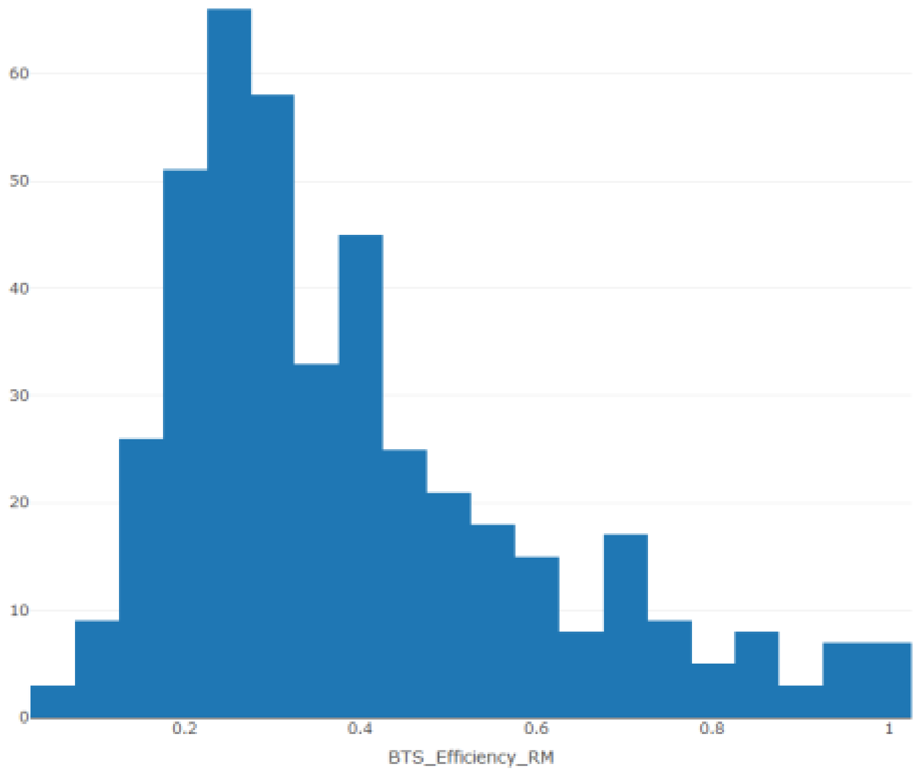


FIGURE 6.10: HISTOGRAM OF EFFICIENCY RESULTS DISTRIBUTION OF THE RM

TABLE 6.20: BTS'S SUPER EFFICIENCY SAMPLE RESULTS

BTS Super Efficiency RM
1.397
1.295
1.182
1.168
1.158
1.149

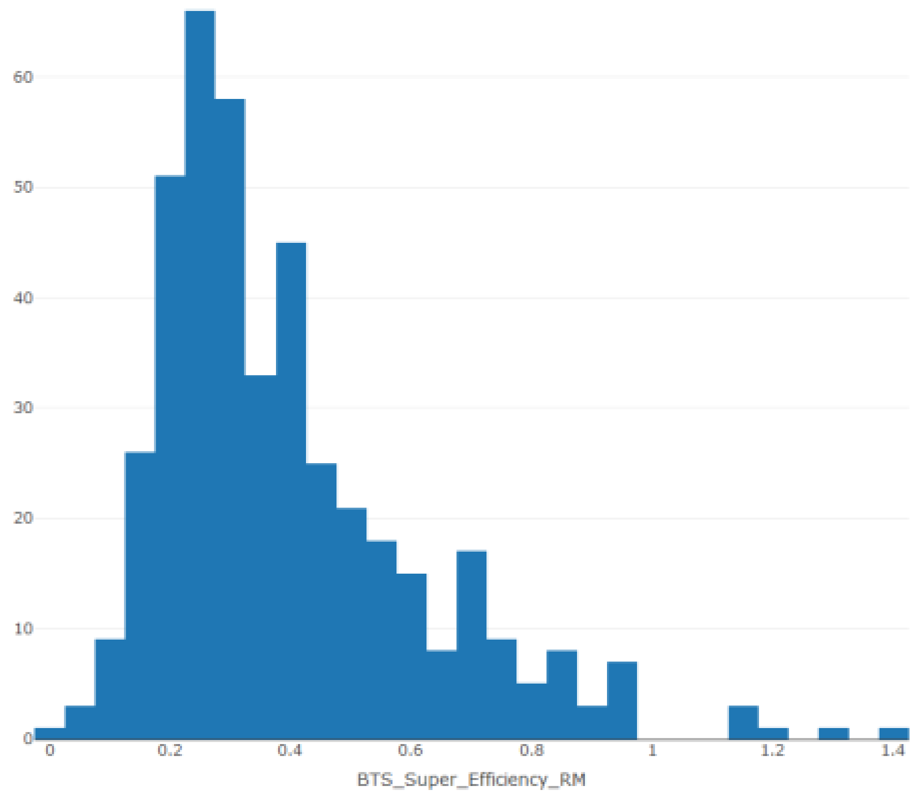


FIGURE 6.11: HISTOGRAM OF SUPER EFFICIENCY RESULTS DISTRIBUTION OF THE RM

TABLE 6.21: BTS'S EFFICIENCY SAMPLE RESULTS

BTS	BTS Efficiency RM	BTS Super Efficiency RM
BTS_1	0.09576	0.09576
BTS_2	0.08637	0.08637
BTS_3	0.5104	0.5104
BTS_4	0.07752	0.07752
BTS_5	0.232	0.232
BTS_6	0.3437	0.3437

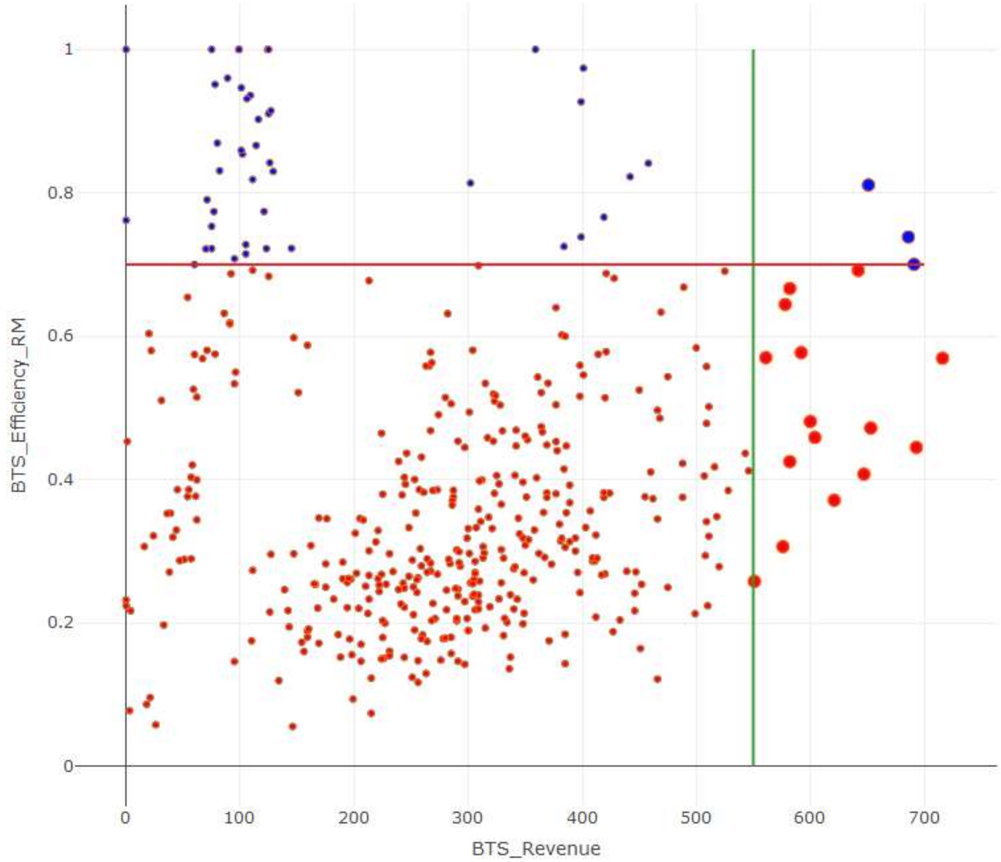


FIGURE 6.12: PERFORMANCE MATRIX TO SHOW THE FOUR CATEGORIES OF THE RM

TABLE 6.22 CATEGORY 1 OF RETAIN MODEL (OPTIMAL BTSS)

BTS	BTS Efficiency RM	BTS Super Efficiency RM	BTS Revenue
BTS_32	0.7383	0.7383	686
BTS_38	0.7001	0.7001	691
BTS_132	0.8109	0.8109	651

TABLE 6.23 CATEGORY 2 OF RETAIN MODEL (HIGH OPPORTUNITY BTSS)

BTS	BTS Efficiency RM	BTS Super Efficiency RM	BTS Revenue
BTS_19	0.4075	0.4075	647
BTS_47	0.5692	0.5692	716
BTS_71	0.371	0.371	621
BTS_75	0.4249	0.4249	582
BTS_76	0.3063	0.3063	576
BTS_77	0.4448	0.4448	693

TABLE 6.24 CATEGORY 3 OF RETAIN MODEL (MEDIUM OPPORTUNITY BTSS)

BTS	BTS Efficiency RM	BTS Super Efficiency RM	BTS Revenue
BTS_1	0.09576	0.09576	21
BTS_2	0.08637	0.08637	18
BTS_3	0.5104	0.5104	31
BTS_4	0.07752	0.07752	3
BTS_5	0.232	0.232	0
BTS_6	0.3437	0.3437	62

TABLE 6.25 CATEGORY 4 OF RETAIN MODEL (LOW OPPORTUNITY BTSS)

BTS	BTS Efficiency RM	BTS Super Efficiency RM	BTS Revenue
BTS_8	0.8186	0.8186	111
BTS_9	0.8419	0.8419	126
BTS_10	0.9465	0.9465	101
BTS_12	0.7	0.7	60
BTS_35	0.8308	0.8308	82
BTS_36	1	1.149	124

TABLE 6.26 SAMPLE OF FINAL RESULTS OF CATEGORY 2 FOR GENERAL MODEL WITH THE REFERENCE SET

BTS	BTS Efficiency RM	BTS_36	BTS_222	BTS_286
BTS_101	0.4809	0	0.0425	0.9574
BTS_105	0.2578	0	0.0425	0.9574
BTS_138	0.4587	0	0.0212	0.9787
BTS_19	0.4075	0	0.0425	0.9574
BTS_191	0.6442	0	0.0425	0.9574
BTS_227	0.4718	0.4482	0.0139	0.5378

6.2.4 Mobility Model (MM)

The same steps that were taken in the general model and Model 1 are also followed in this model. The inputs and outputs of the model are illustrated in Figure 6.13. Table 6.27 shows a sample of efficiency and super-efficiency, in which eighteen branches are efficient. Additionally, Tables 6.27-6.34 and Figures 6.14-6.16 display the results of this model.

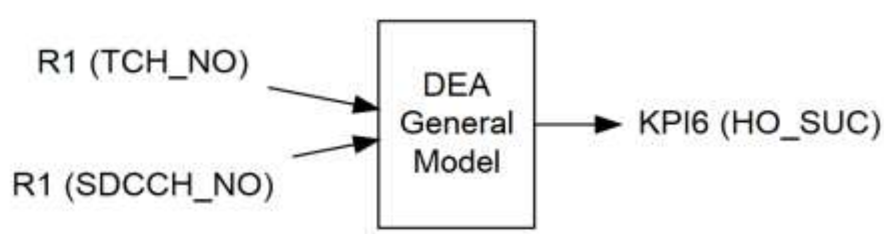


FIGURE 6.13: MOBILITY MODEL DIAGRAM

TABLE 6.27 VRS-OUTPUT EFFICIENCY SAMPLE RESULTS

Index	BTS Efficiency MM
BTS_1	0.03281
BTS_2	0.01641
BTS_3	0.1895
BTS_4	0.009455
BTS_5	0.08253
BTS_6	0.101

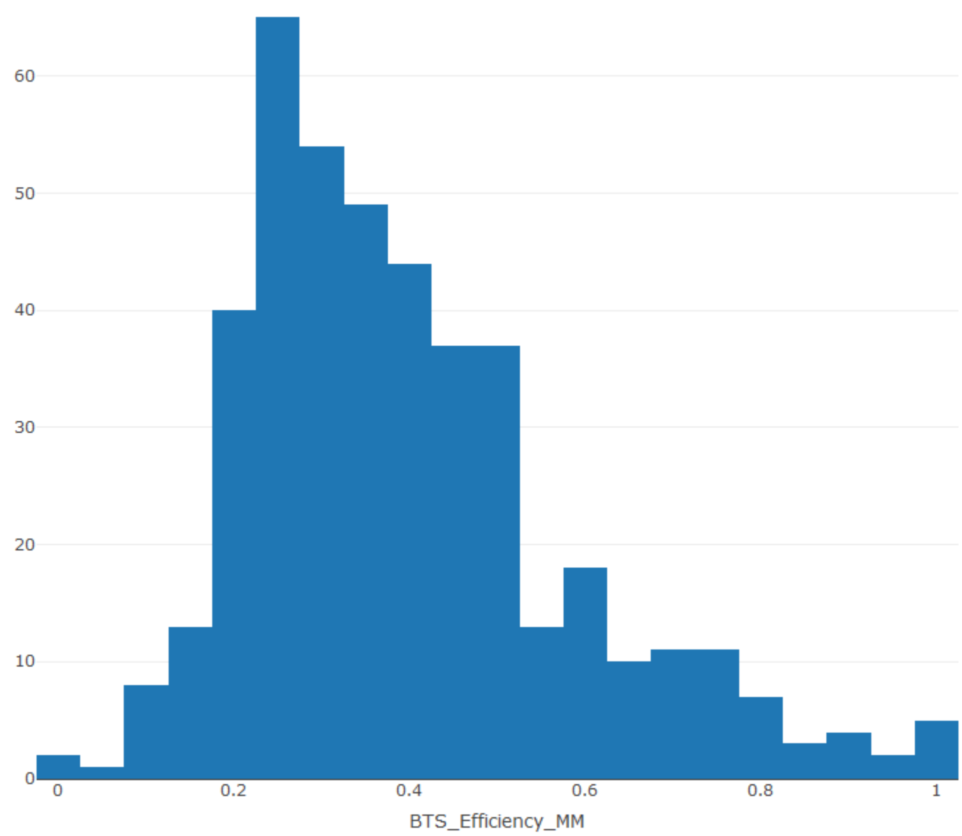


FIGURE 6.14: HISTOGRAM OF EFFICIENCY RESULTS DISTRIBUTION OF THE MM

TABLE 6.28 BTS'S SUPER EFFICIENCY SAMPLE RESULTS

BTS Super Efficiency MM
1.318
1.206
1.117
1.107
0.9364
0.9305

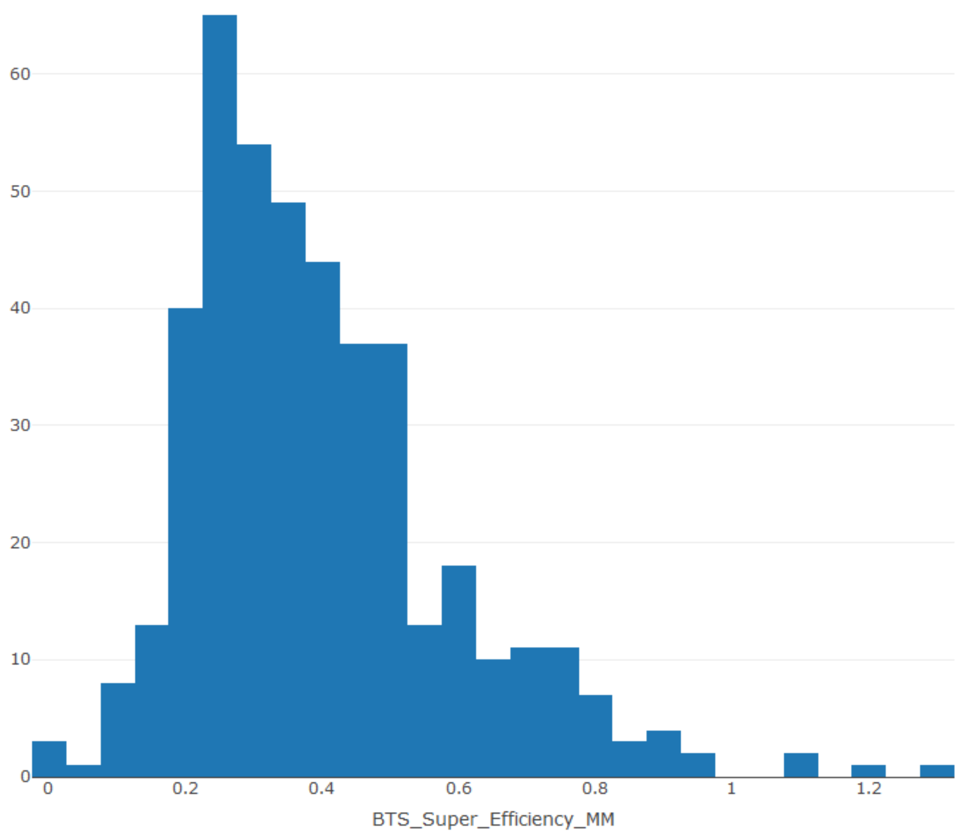


FIGURE 6.15: HISTOGRAM OF SUPER EFFICIENCY RESULTS DISTRIBUTION OF THE MM

TABLE 6.29 BTS'S EFFICIENCY SAMPLE RESULTS

BTS	BTS Efficiency MM	BTS Super Efficiency MM
BTS_38	1	1.107
BTS_229	1	1.117
BTS_284	1	1.318
BTS_326	1	1.206

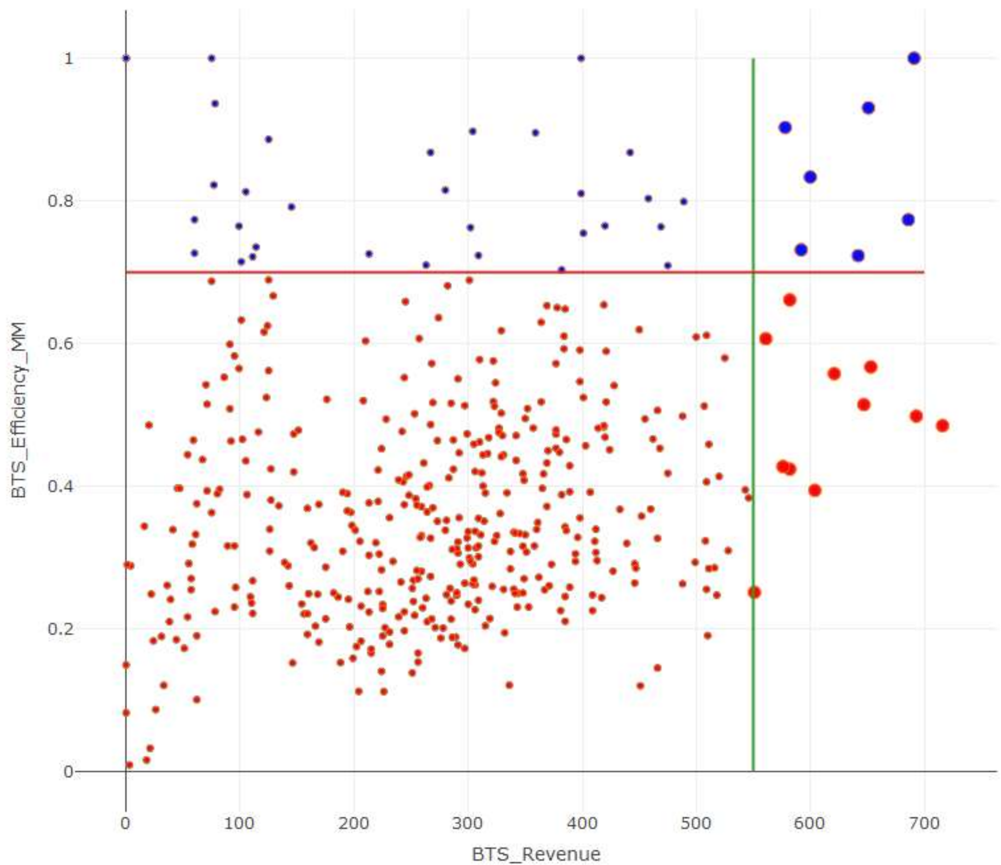


FIGURE 6.16: PERFORMANCE MATRIX TO SHOW THE FOUR CATEGORIES OF THE MM

TABLE 6.30 CATEGORY 1 OF MOBILITY MODEL (OPTIMAL BTSS)

BTS	BTS Efficiency MM	BTS Super Efficiency MM	BTS Revenue
BTS_32	0.7736	0.7736	686
BTS_38	1	1.107	691
BTS_101	0.8334	0.8334	600
BTS_132	0.9305	0.9305	651
BTS_191	0.9029	0.9029	578
BTS_302	0.7314	0.7314	592

TABLE 6.31 CATEGORY 2 OF MOBILITY MODEL (HIGH OPPORTUNITY BTSS)

BTS	BTS Efficiency MM	BTS Super Efficiency MM	BTS Revenue
BTS_19	0.5145	0.5145	647
BTS_47	0.485	0.485	716
BTS_71	0.5578	0.5578	621
BTS_75	0.4241	0.4241	582
BTS_76	0.4277	0.4277	576
BTS_77	0.4983	0.4983	693

TABLE 6.32 CATEGORY 3 OF MOBILITY MODEL (MEDIUM OPPORTUNITY BTSS)

BTS	BTS Efficiency MM	BTS Super Efficiency MM	BTS Revenue
BTS_1	0.03281	0.03281	21
BTS_2	0.01641	0.01641	18
BTS_3	0.1895	0.1895	31
BTS_4	0.009455	0.009455	3
BTS_5	0.08253	0.08253	0
BTS_6	0.101	0.101	62

TABLE 6.33 CATEGORY 4 OF MOBILITY MODEL (LOW OPPORTUNITY BTSS)

BTS	BTS Efficiency MM	BTS Super Efficiency MM	BTS Revenue
BTS_8	0.7217	0.7217	111
BTS_10	0.7148	0.7148	101
BTS_12	0.7738	0.7738	60
BTS_15	0.7267	0.7267	60
BTS_64	0.7258	0.7258	213
BTS_88	0.7035	0.7035	382

TABLE 6.34 SAMPLE OF FINAL RESULTS OF CATEGORY 2 FOR GENERAL MODEL WITH THE REFERENCE SET

BTS	BTS Efficiency MM	BTS_38	BTS_326
BTS_105	0.2514	1	0
BTS_138	0.3942	0.6666	0.3333
BTS_19	0.5145	1	0
BTS_227	0.5673	1	0
BTS_259	0.6068	1	0
BTS_373	0.6613	1	0

6.2.5 Service Integrity Model (SIM)

The same steps that were taken in the general model and Model 1 are also followed in this model. The inputs and outputs of the model are illustrated in Figure 6.17. Table 6.35 shows a sample of efficiency and super-efficiency, in which eighteen branches are efficient. Additionally, Tables 6.35-6.42 and Figures 6.18-6.20 display the results of this model.

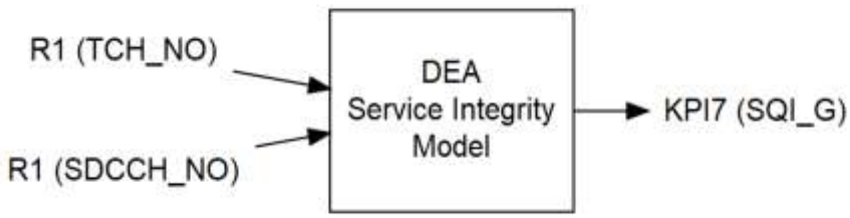


FIGURE 6.17: SERVICE INTEGRITY MODEL DIAGRAM

TABLE 6.35 VRS-OUTPUT EFFICIENCY SAMPLE RESULTS

Index	BTS Efficiency SIM
BTS_1	0.159
BTS_2	0.1019
BTS_3	0.3037
BTS_4	0.06626
BTS_5	0.3548
BTS_6	0.421

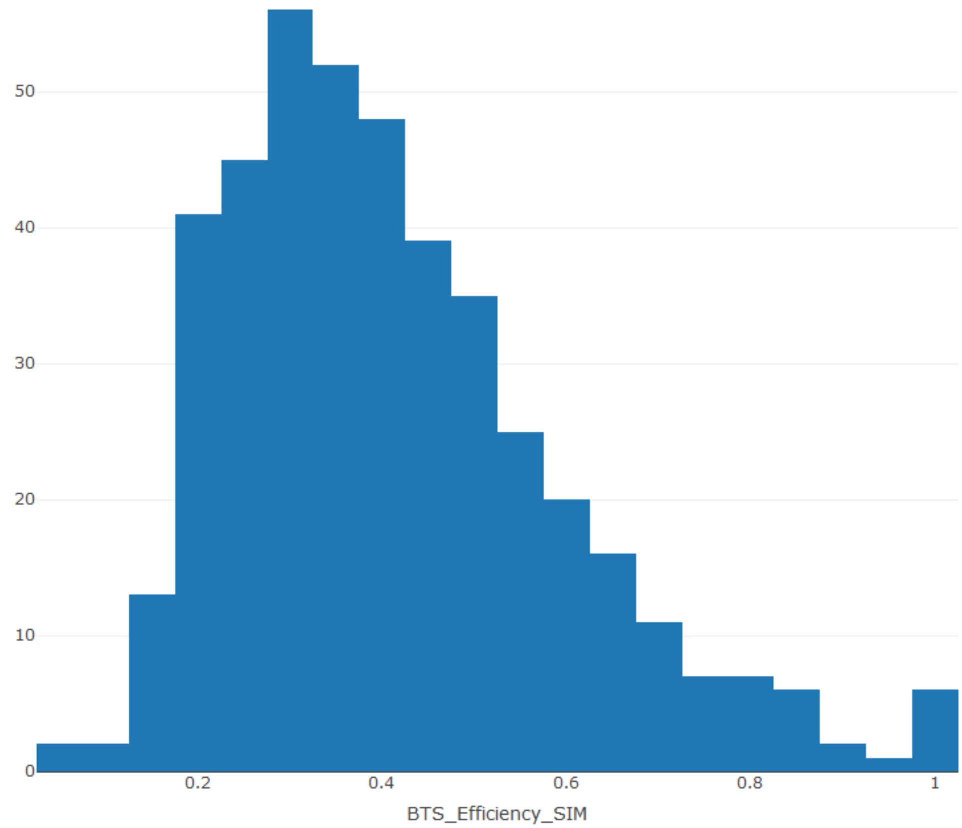


FIGURE 6.18: HISTOGRAM OF EFFICIENCY RESULTS DISTRIBUTION OF THE SIM

TABLE 6.36 BTS'S SUPER EFFICIENCY SAMPLE RESULTS

BTS Super Efficiency SIM
1.243
1.186
1.168
1.071
0.9873
0.9338

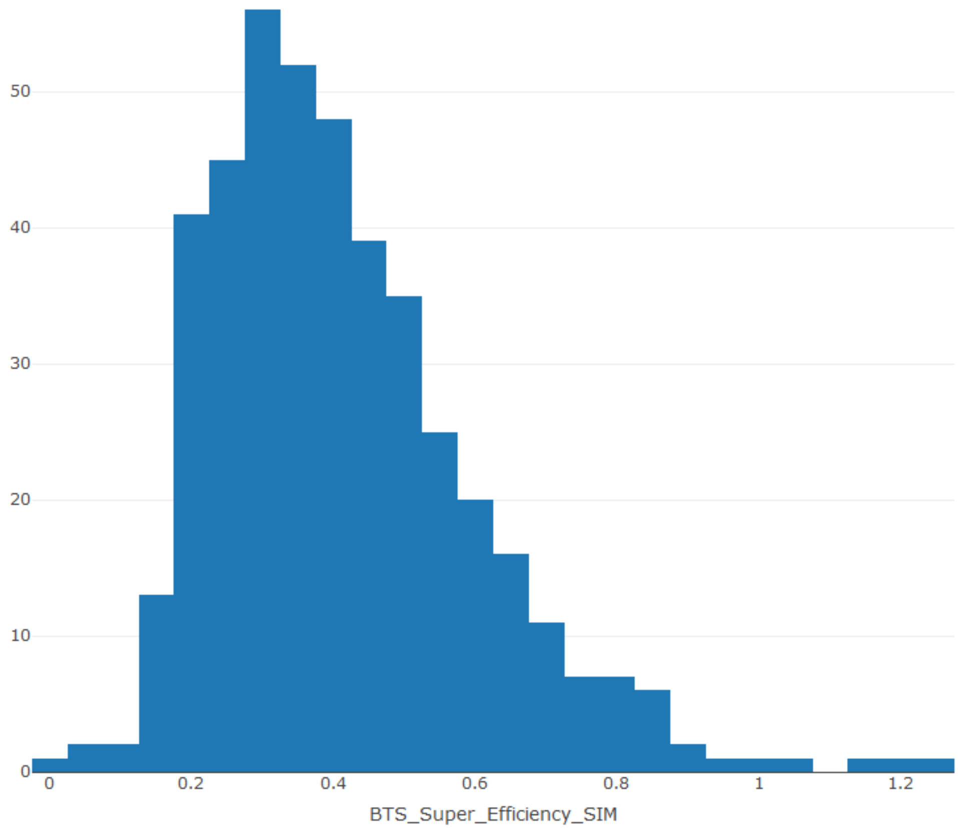


FIGURE 6.19: HISTOGRAM OF SUPER EFFICIENCY RESULTS DISTRIBUTION OF THE SIM

TABLE 6.37 BTS'S EFFICIENCY SAMPLE RESULTS

BTS	BTS Efficiency SIM	BTS Super Efficiency SIM
BTS_32	1	1.071
BTS_222	1	1.168
BTS_285	1	1.243
BTS_286	1	1.186

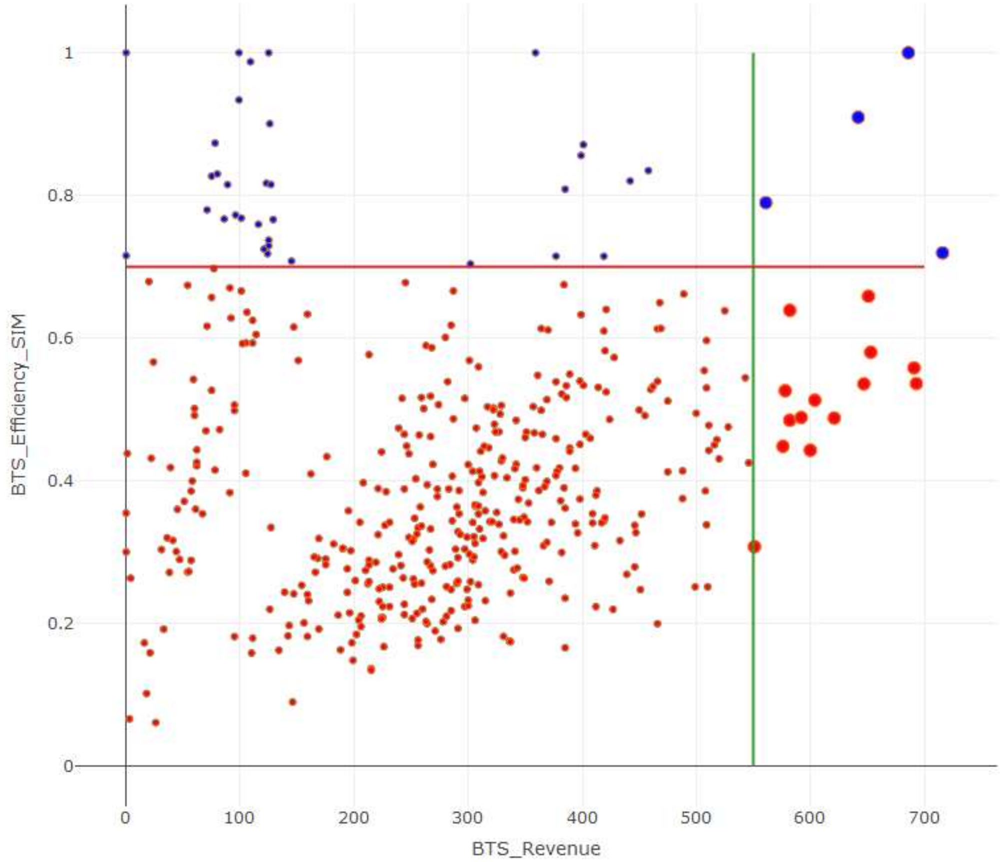


FIGURE 6.20: PERFORMANCE MATRIX TO SHOW THE FOUR CATEGORIES OF THE SIM

TABLE 6.38 CATEGORY 1 OF SERVICE INTEGRITY MODEL (OPTIMAL BTSS)

BTS	BTS Efficiency SIM	BTS Super Efficiency SIM	BTS Revenue
BTS_32	1	1.071	686
BTS_47	0.7196	0.7196	716
BTS_259	0.7899	0.7899	561
BTS_304	0.9095	0.9095	642

TABLE 6.39 CATEGORY 2 OF SERVICE INTEGRITY MODEL (HIGH OPPORTUNITY BTSS)

BTS	BTS Efficiency SIM	BTS Super Efficiency SIM	BTS Revenue
BTS_19	0.5359	0.5359	647
BTS_38	0.5583	0.5583	691
BTS_71	0.488	0.488	621
BTS_75	0.4848	0.4848	582
BTS_76	0.4483	0.4483	576
BTS_77	0.5363	0.5363	693

TABLE 6.40 CATEGORY 3 OF SERVICE INTEGRITY MODEL (MEDIUM OPPORTUNITY BTSS)

BTS	BTS Efficiency SIM	BTS Super Efficiency SIM	BTS Revenue
BTS_1	0.159	0.159	21
BTS_2	0.1019	0.1019	18
BTS_3	0.3037	0.3037	31
BTS_4	0.06626	0.06626	3
BTS_5	0.3548	0.3548	0
BTS_6	0.421	0.421	62

TABLE 6.41 CATEGORY 4 OF SERVICE INTEGRITY MODEL (LOW OPPORTUNITY BTSS)

BTS	BTS Efficiency SIM	BTS Super Efficiency SIM	BTS Revenue
BTS_7	0.7373	0.7373	125
BTS_9	0.9005	0.9005	126
BTS_10	0.7682	0.7682	101
BTS_36	0.7183	0.7183	124
BTS_44	0.7725	0.7725	96
BTS_49	0.767	0.767	86

TABLE 6.42 SAMPLE OF FINAL RESULTS OF CATEGORY 2 FOR GENERAL MODEL WITH THE REFERENCE SET

BTS	BTS Efficiency SIM	BTS Revenue	BTS_222	BTS_286
BTS_101	0.4428	600	0.0425	0.9574
BTS_105	0.3077	551	0.0425	0.9574
BTS_132	0.6587	651	0.0212	0.9787
BTS_138	0.513	604	0.0212	0.9787
BTS_19	0.5359	647	0.0425	0.9574
BTS_191	0.5262	578	0.04255	0.9574

6.3 Further Analysis of the General Model

I ran the multi regression analysis between the efficiency's results and the model factors, and the model summary below shows that the inputs have a negative coefficient estimate while the outputs mostly have a positive coefficient estimate. This confirms the principles of the idea of minimizing the inputs and maximizing the output for better efficiency. However, in this model, there is a high multicollinearity among variables, so we cannot rely on these results. Also, the result shows that some factors are not significant, which leads to think about the multi-correlation between the KPIs. One of the solutions to improve the regression model is to apply the stepwise regression to drop the non-significant factors, but this will not help to measure the efficiency of the BTS since all the factors are important.

```
Call:
lm(formula = BTS_Efficiency_GM ~ ., data = RegData_2)


Residuals:
     Min       1Q   Median       3Q      Max 
-0.14882 -0.04022 -0.02119  0.01349  0.65969 


Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.508e-01  2.419e-02  14.503  < 2e-16 ***
TCH_NO      -3.964e-04  6.217e-05  -6.376 4.76e-10 ***
SDCCH_NO    -6.094e-03  6.526e-04  -9.337  < 2e-16 ***
TCH_T       -1.761e-03  1.191e-03  -1.479  0.14000    
SDCCH_T      3.393e-03  1.211e-03   2.802  0.00532 ** 
TCH_SUCC     1.709e-04  4.012e-05   4.259 2.54e-05 ***
SDCCH_SUC    1.083e-05  1.553e-05   0.697  0.48594    
RACH_SUC    -2.140e-05  8.165e-06  -2.622  0.00907 ** 
HO_SUC       1.484e-04  9.534e-06  15.562  < 2e-16 ***
SQI_G        7.154e-05  2.253e-05   3.176  0.00160 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.07532 on 424 degrees of freedom
Multiple R-squared:  0.8793,    Adjusted R-squared:  0.8768 
F-statistic: 343.4 on 9 and 424 DF,  p-value: < 2.2e-16
```

To gain some insights, I ran the correlation matrix using efficiency results, and re-scaled the tuning parameters. Figure 6.21 shows the results.

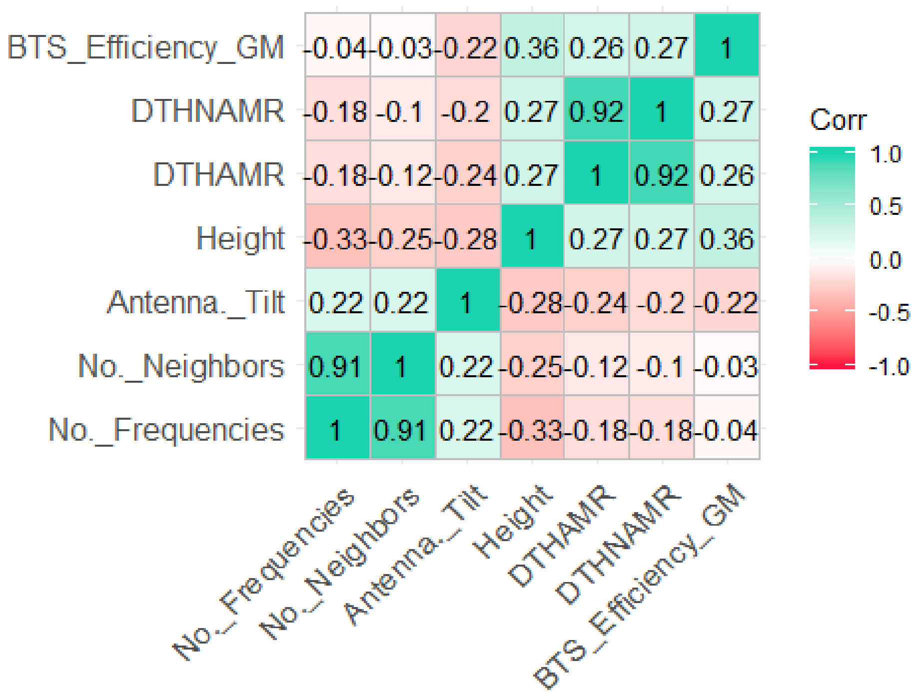
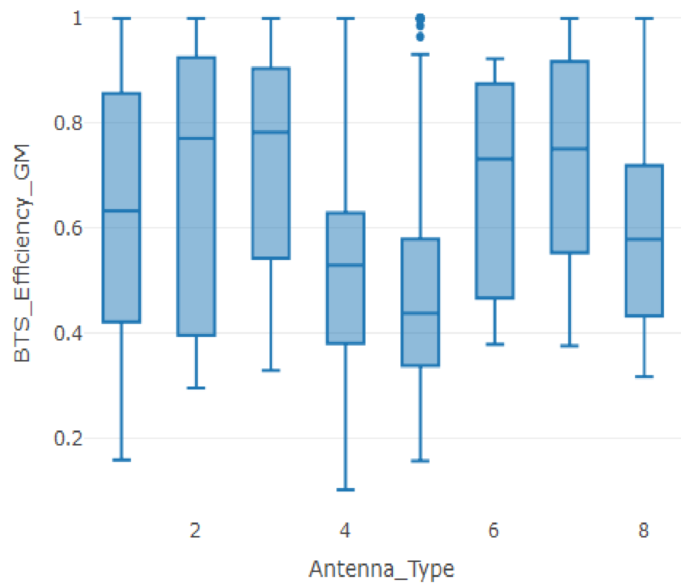
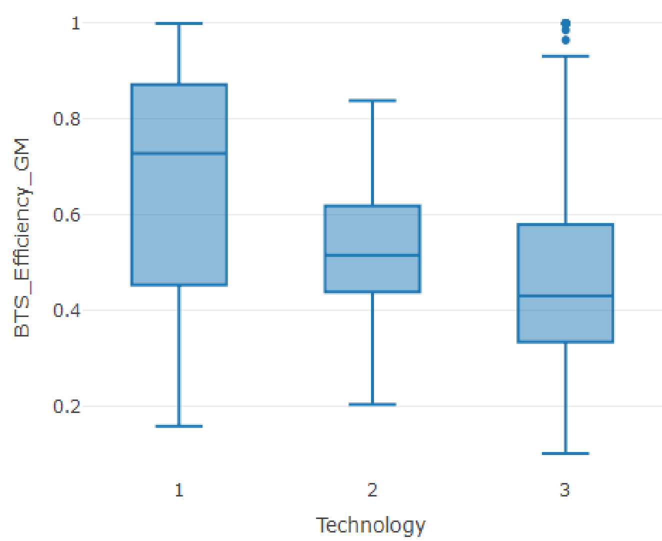


FIGURE 6.21: CORRELATION MATRIX USING EFFICIENCY RESULTS AND RE-SCALED TUNING PARAMETERS

For the coded tuning parameters group, I plotted the box plot, for each one with efficiency results as shown in Figure 6.22. These plots help the decision maker to better understand each parameter. For instance, there might be an issue with the RBS type 2 where the average efficiency of all of them is around 0.45, while the plot shows the average efficiency of RBS type 3, which means this type is very good.


1
0.8
0.6
0.4
0.2
BTS_Efficiency_GM
2
4
6
8
Antenna_Type


1
0.8
0.6
0.4
0.2
BTS_Efficiency_GM
1
2
3
Technology

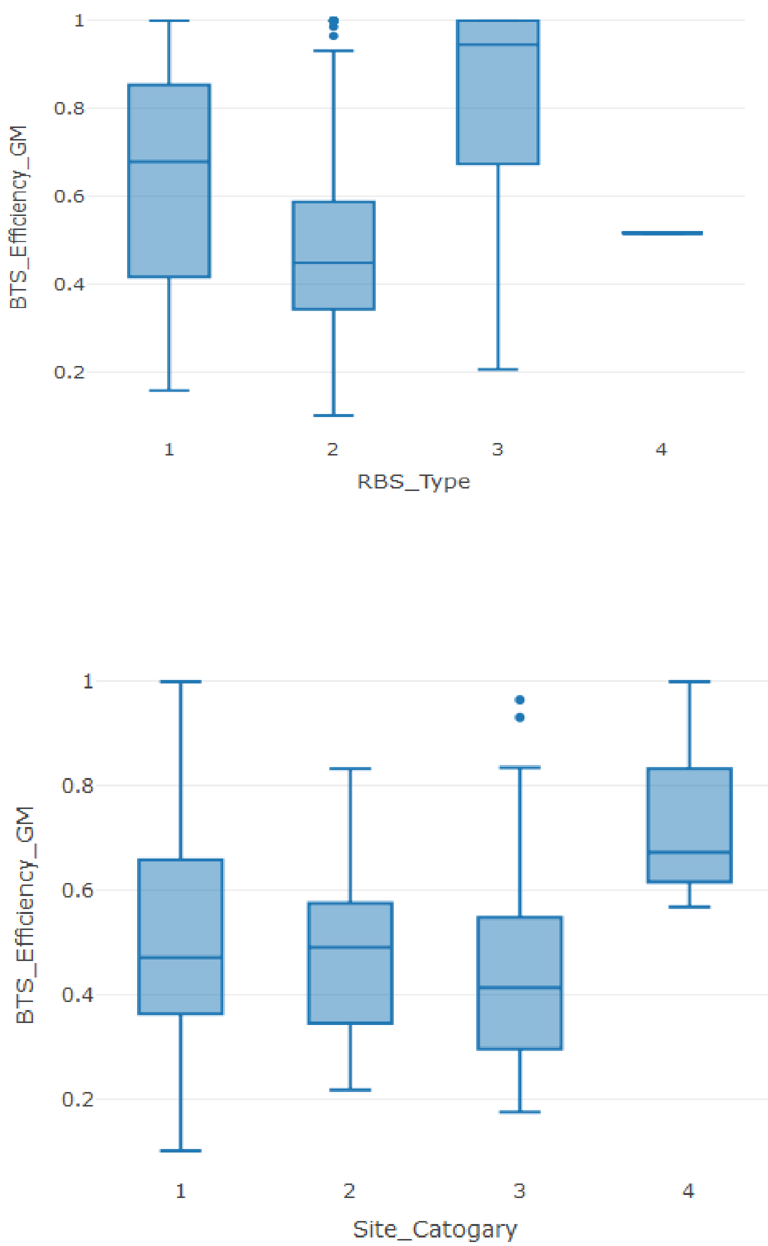


FIGURE 6.22: BOX PLOT FOR THE CODED TUNING PARAMETERS AND EFFICIENCY RESULTS

Chapter 7 Research Validation

7.1 Expert Panel Procedures

The accuracy and credibility of the model are critical in complex systems, yet difficult to manage (Ford and Sterman 1998). Expert knowledge is one of the methods to validate the model and results and has been widely used to support decision making in many kinds of research and applications (Nemet *et al.* 2017). Even for research where data is available, and some statistical analysis methods are used, the expert's opinions have significant value in the interpretation of results. Many papers (Seiford 1997, Aruldoss *et al.* 2013, Farantos 2015) highlighted that one of the limitations in DEA is a lack of statistical tests to validate the results.

To challenge its limitation, aggregating expert judgments as inputs into the research process will be adopted. The expert panel will be involved twice in validating the model, and the Qualtrics survey software will be used to ask experts to quantify the inputs, outputs, and validate the model overall. Additionally, the results will be validated with the experts as well as through a variety of statistical tests in regression to differentiate the individual coefficients' impact on the model and measure correlation.

7.1.1 Experts

The focus of this research will be on building the right model and providing guidance based on the analysis. Therefore, the validation step using experts in this field is important in the process. Receiving feedback from the cellular telecom experts is essential to deliver valuable results. The selection experts are telecom engineers who are qualified through their specific knowledge in radio cellular network and with relevant work experience in telecom cellular sector. Appendix D shows the invitation letter that has been sent to list of experts to give feedback and validate the models.

7.1.2 Expert Validation Process Step 1

I used Qualtrics Software to send the survey, which includes 6 questions to evaluate the initial models and get feedback from the experts and make any changes to the model if needed. Appendix E shows the survey questions. Then based on the experts' feedback I update my models, and Appendix F shows the raw experts' feedback. From the charts, it seems most of the experts agree with the inputs and outputs, and most of the disagreement about the inputs was a misunderstanding; therefore, I changed the name of the inputs from KPIs to Resource.

7.1.3 Expert Validation Process Step 2

After I got my results and I wrote my analysis and recommendation, I needed to evaluate my results. Due to the sensitivity of the network and the provider I could not recommend on the real network, and because I wanted to physically make these changes on the system, I used the experts to validate the results and incorporate the recommendations from my analysis, check for feedback, and determine if there were more changes. Most of the feedback was positive and in agreement with trying these changes on the network to see the real improvement.

7.2 Generalizing the Research

It is important to have an open approach to have a valuable contribution, so this research can be generalized. Below are the three scenarios to explore.

- First, it is to be used in another country or cellular operator. It is not specific for the Libyan provider, Almadar Aljadid Co. The model can be easily adopted since the KPIs and the parameters that the research used are standard, and the cellular 2G is a global standard technology and most of the operators are facing similar challenges.

- Second, the model can cover other mobile technologies such as 3G, 4G, and 5G. In these cases, users will need to change the model in terms of the inputs and outputs based on the most important KPIs. Additionally, this model focuses on the voice KPIs since the 2G is heavily focused on voice, but the newest technology the data is more important which means the focus will need to be changed.

- Third, the research can be applied to other industries and domains in the service industries, which might share a similar environment and business approach. In this context, we can use the fast-food industry as an analogy to the mobile telecom industry to generalize my model for nontechnical people (Dabab *et al.* 2019). Historically, the telephone system developed from a fixed telephone (a landline telephone) that uses a metal wire and fixed telephone device that is typically located in a place such as a home. To receive the cellular services, the person must be in the situation in that location, similar to how customers must be in the restaurants to receive the foodservice. However, the new technology of drive-throughs allows customers to purchase products and get the services just bypassing the restaurant without leaving their cars. This process is similar to the development of telephone services, where the mobile phone can operate wirelessly. Based on this analogy, we can match the BTS units in the cellular network to the restaurant's branches in the fast-food chain like McDonald's.

In practice, I was able to implement a similar model and work with the Campus Sustainability Office at Portland State University. The PSU Sustainability Dashboard shows the proposed DEA efficiency benchmarking modeling to measure building efficiency using the fifty-eight buildings of the PSU campus. The model will give the best practice recommendations as operation management strategy changes and other factors as well, to improve the inefficient building. The issue was with the method of a EUI, which is common practice and one way to compare efficiencies across sectors. It does not provide a comprehensive picture of a building's actual efficiency. Looking at the multidimensional aspects of a building can lead to a more robust model to help give us a clearer picture of the building's actual efficiency. This model provides multiple ways to analyze utility data and provide some best practice research that can help inform decision making to move towards more sustainable operations and maintenance practices on campus. The results of this work will assist the operation management team to understand the best practices of energy consumption benchmarking for the campus buildings. This will maintain the sustainable operations and facilities on campus and track the utilities to help practitioners and policymakers.

Chapter 8 Discussion

8.1 Results and Examination

This analytic approach allows operators with multiple input and outputs to compare the efficiency of the BTSs. This allows them to know the best practices for the BTSs, and for the network efficiency frontier to determine the inefficient resources in order to make the right decisions about them. The models are assessing the performance of the BTSs based on the output-oriented method and the concept of VRS (Banker, Charnes, & Cooper 1984).

While the individual KPIs provide sufficient insights to the degree of use radio indicators, this analysis suggests detailed information on the relative performance of each BTS, which leads to high-level insight for network performance improvements. The efficiency score ranges from 1 to 0 and 1 is efficiency. Appendix B shows the efficiency of the BTSs in the five models including the BTS index and 5 efficiency results. After determining the efficiency score for each BTS, the super-efficiency was found to differentiate between the efficient BTSs, and the super efficiency tables for each model in Chapter 6 illustrate that. Across the five models, only one BTS, BTS_219, is efficient. It is interesting since the super efficiency of this one is 1. This highlights that the highest super-efficient BTS is not always the best, but sometimes it means that maybe it was overloaded or taking more than the capacity. This might extend research in the future.

As a second step in the analyses, the performance matrix was implemented to get the four categories, and these four groups of the Decision-Making Units (DMU) were based on 0.7 efficiency and 550 revenue thresholds, so the recommendations are divided into four main points. These points are course of action guidelines for the top management:

- The first group (Optimal BTSs): these are the most important BTSs since they have high-level customer satisfaction, and they make a high profit.
- The second group (High Opportunity BTSs): these have the priority for the top management to undertake some action for efficiency enhancements. The reason is that even though they do not perform well and have low efficiency, they are making high profits. Therefore, by improving the efficiency of these branches, we will have a high opportunity for increasing profitability.
- The third group (Might Opportunity BTSs): these have the second priority for actions to enhance the efficiency to move them to group one or group two. Basically, after enhancing the efficiency, we might get more profit, or it will be the same.
- The fourth group (Low Opportunity BTSs): these branches, even though the customers receive satisfactory services, still do not make enough profit.

However, since we need or sometimes have to provide the services everywhere, probably we cannot close them, but we might relocate them.

Because of the importance of Category 2, in the recommendation section of the dissertation, I will focus on this group as an area where more actions can be taken in terms of efficiency, and to conduct a deep analysis of these 7 BTSs in the general mode. Appendix C shows the reference set for Category 2 (high opportunity BTSs) of each model with the weights of the reference count. Looking at the reference set of each inefficient branch that is in the high opportunity group, we can suggest some actions based on the parameter information, which is the second group of the tuning parameters dataset. I take them as an example of the recommendation to improve efficiency since they have the highest profitability, and Chapter 9 illustrates that.

These models and groups explain the best practices in terms of the significance of each BTS in relation to other inefficient BTSs. The potential usage of the reference set is to give guidelines for the network engineers. They can improve the inefficient BTSs by comparing the configuration with the BTSs in the references set for improvement initiatives to achieve a high level of network optimization. For instance, in the general model, the BTS 71 and BTS 75 have almost the same efficiency, but they have a different reference set that should be used to gain suggestions for better practices. The reference set will provide opportunities for given improvements that the network engineers can use. Also, network engineers can validate the results by implementing some changes in the inefficient BTSs based on the setting of the BTSs in the reference set, and then check the new data later to see if there is the desired improvement in the efficiency of the inefficient BTS.

The statistical and regression analysis was conducted as a third step to gain insights and provide specific direction. With these results, we can suggest enhancements to the BTSs to maximize the efficiency of the inefficient BTSs based on best practices BTSs, which helps the operators spend more effort and time on those areas. Some of these insights can be summarized as:

- Most of the BTSs, which have RBS Type 3, have high efficiency while the RBS Type 2 has low efficiency.
- The BTSs within Site Category 4 have better efficiency compared with other categories.
- BTSs with Antenna Types 4 and 5 tend to have low efficiency, so check these types if there are any manufacturing issues.
- There is a negative correlation between the efficiency of the BTS and the tile of the antenna, which makes sense, especially in the urban area. While there is a positive correlation between the efficiency and the height of the

tower, if we put artificial BTS with more height we will see something different.

8.2 An Appropriate or Inappropriate Model

It is difficult to evaluate performance and efficiency in the service industry through a single indication. Therefore, it is very important to establish an evaluated method that includes multiple indications. Thus, due to the fact that genuine customer service can encourage customers to come again, while a bad service experience could be enough to convince a customer to never return, it is critical to the cellular providers to assist the performance of the critical assets because those operational improvements are reflected in provider's performance. Additionally, because mobile services are quick to serve, they have many challenges with delivering a high level of customer service and quality of service. With these needs, building a model to evaluate the overall efficiency regarding customer satisfaction for BTSs creates a brand identity that stands up among competition.

The nature of the cellular phone network functions differently than the traditional fixed phone business. In the traditional customer satisfaction measurement in fixed service, people evaluate the efficiency based on many factors, such as cost, maintenance, etc. However, due to the new way of service in the phone industry, the customers are concerned with many things, including the flexibility to move, the quality of the voice, and the data speed. The telecommunication branches' goal is to exceed those expectations to maintain efficient service. However, this research focuses on 2G technology data and does not include the data. This might be a future work consideration to make the model more robust since it is difficult to distinguish whether this performance is attributable to the efforts of the efficient voice or data.

In operations, we should understand reasonably well the relationships between operational inputs and outputs (Johnston and Jones 2004). Where all the inputs are uncontrollable, the DMUs are equally faced with difficult or more difficult operating environments in the output-oriented approach. In the foodservice industry, for instance, uncontrollable factors might include a restaurant's maximum seating capacity, parking availability, and the number of nearby competitors (Reynolds and Thompson, 2002). However, in the case of using controllable inputs in the model, the high performance becomes a function of management decisions, which leads in turn to identifying best practices.

Productivity measurement, monitoring, and improvement lead to overall gains to companies. In terms of profitability, leading service firms focus on achieving productivity gains as an overarching objective (Eccles 1991). Therefore, integrating the profitability in the performance matrix is an effective contribution and makes the research unique. Thus, one of the reasons that this study is relevant to the leading research is that cellular networks in particular have attracted growing attention due to the high risk for disruptive innovation. While some mobile providers rely on analyzing social media posts across the top three social channels and call centers to evaluate the services, this model counts on data measurements and best practices to build efficiency. For this study, we provide a representative sample of area data that interprets the service flow through the BTSs, and the levels of the operation in the 434 BTSs. The recommendation of actions will lead to an increase in the efficiency of BTSs in terms of recommendations and suggestions to the high opportunity BTSs group.

8.2.1 The Analogy with Another Application

Historically, the telephone system developed from a fixed telephone (a landline telephone) that used a metal wire and fixed telephone device typically located in a place such as a home. To get the services, the person has to be in the same location as the phone line. Similar to the idea of the restaurants where people go to get the food. However, the new technology, the drive-thru, allows customers to purchase products and get the services just bypassing the restaurant without leaving their cars. This process is similar to what happened to the telephone services with a mobile phone that wireless operated. Based on this analogy, I matched the BTS units in the cellular network to the restaurant's branches in the fast-food chain like MacDonald's. Figure 8.1 illustrates the main components of the cellular network. Similarly, Figure 8.2 illustrates the main components of the fast-food chain.

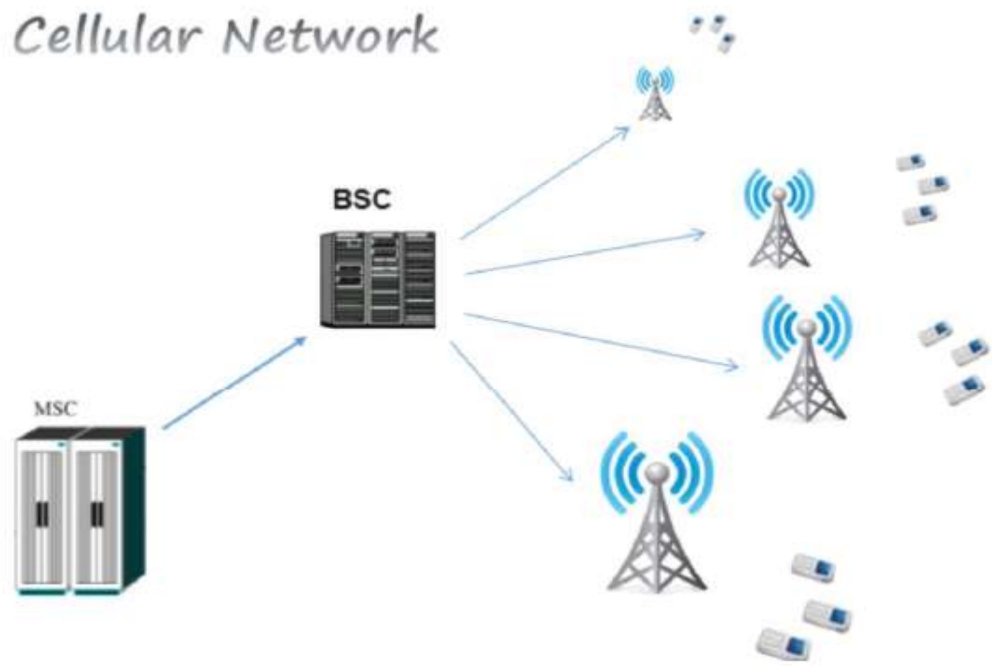


FIGURE 8.1: CELLULAR NETWORK COMPONENTS

FIGURE 8.2: FAST-FOOD CHAIN COMPONENTS

From both Figures 8.1 and 8.2, we can conclude these assumptions and analogies:

- The mobile switching center (MSC) is similar to a warehouse.
- The Base Station Controller (BSC) is equivalent to a distribution center.
- The base transceiver station (BTS) is equivalent to a restaurant.
- The interface connects and delivers the signal between the three main parts of the cellular network, and on the other hand, trucks deliver the food between the three main components.
- The customers are people who are the same.

Thus, some industries and applications might share a similar environment and business approach. In the context of that, these industries sometimes have a similar problem that we can solve by using the same technique. Thus, the complex application can be simplified using the analogy with an understandable application to understand the results and the implications. In this context, I used the fast-food industry as an analogy to my application, which is the mobile telecom industry, to generalize my model for non-technical people.

8.2.1.1 BTSs and Restaurants Comparison

In the mobile network, the signal is delivered using Abis-interface through BTS. Similarly, trucks deliver the food to the restaurant through the distribution center. In other words, the BTS is the part of the network where the subscribers get their information from, and in case of the food industry, how customers get food from the restaurant. We can visually imagine how the BTS is similar to restaurants in terms of analogs, and many factors affect the quality of service in both examples. Some of them are similar in concept and others are different, which can be summarized into:

- **Similarities:**
  - In both systems, resource efficiency has a direct impact on the quality of service (QoS). For instance, unstable and limited resources

may lead to undesirable and potentially disruptive application behavior which means more issues.

– Both industries build on customer satisfaction, so not maintaining high performance of services would induce customer dissatisfaction toward the provider.

– Both BTS and the restaurant are the interface component with the customers since they do not know or deal with other parts of the network. As a result, it is imperative to focus on handling the interface and improving the efficiency of these to improve the QoS.

– There are large and small operators across the network, which is applied to both cases. In other words, the restaurant's branches are similar to the BTS in that they have different capacities and surrounding environments.

– Overcapacity of both the restaurant and BTS may lead to low service quality, which is why the providers are interested in the quality of their service, and why they make sure to provide the required space for customer capacity. Also, the capacity of the size will control the number of subscribers that can be served at the same time. The number of the frequencies or TRUs are similar to the lines and windows in the drive-thru case.

- A study emphasizes the importance of understanding the traffic pattern over 24 hours, and it highlighted that the peak hour of a system, the hour when the system handles the highest traffic, needs more focus (Oladeji *et al.* 2013). This is similar to the restaurant case.

- **Differences:**
  - Some factors, especially in the parameter group, were matched in terms of general style; however, they have different functions or influence. For instance, the height of the tower in the mobile system has a significant impact on the service, but the height of the advertisement for a restaurant sign or billboard has a minimal effect on the number of orders the restaurant receives, and has no influence on the QoS of the branch.
  - In most cases, the customer of the telecom provider relies on one provider for a period of time, as customers do not switch to another operator every day. On the other hand, customers in the food industry can change daily, and frequently try a different kind of restaurant. But here we assume that the customer eats at the same chain in different locations. And, in Libya, as I pointed out before people have lines with both providers, and it's natural that

customers switch and use another sim card in a different location where the services are inadequate. With this case, this feature turns out to be almost similar.

- Regarding the models which, in this report, is a fast-food efficiency analysis, I use three types: a general model, a model that represents the precision and correctness, and a model of mobility and fluency. However, analyzing the BTS efficiency includes more KPIs, and the models will be divided based on the service quality indicators to accessibility, retainability, mobility, and service integrity. The last model comprises all factors.

Chapter 9 Recommendation

9.1 Improving the Inefficient BTSs of GM

To express the recommendation for radio optimization engineering, I removed the zero columns in the lambda table for each BTS of the 7 BTS's in the high opportunity group in the general model with its peer to tune the parameters. Tables 9.1, 9.2, 9.3, 9.4, 9.5, 9.6, 9.7 include each of these 7 BTSs with their peer BTSs with the tuning parameters with which we can highlight the recommended parameters that should be changed. Also, I recommend crossing the BTS_286 in the set references since the tuning parameters show that this BTS does not match the others. My recommendations are:

- For BTS_105: The antenna tilt should be changed from 4 to 0, or height of the tower should be increased to approximately the 30s. Also, the BTS should define more neighbors to the site from 60 to something in the 70s. Lastly, the DTHNAMR should be changed to be 45.

TABLE 9.1: TUNING PARAMETERS DATA OF THE REFERENCE SET OF BTS_105

Index	No. Frequencies	No. Neighbors	Site Category	RBS Type	Technology	Antenna Type	Antenna. Tilt	Height	DTHAMR	DTHNAMR
BTS_105	76	60	2	2	3	5	4	23.5	45	15
BTS_222	76	73	1	2	3	5	0	23.5	45	45
BTS_286	48	27	1	3	1	1	4	34	60	38
BTS_304	82	87	1	2	3	5	2	26.5	56	56
BTS_313	86	81	1	2	3	5	6	40	10	10

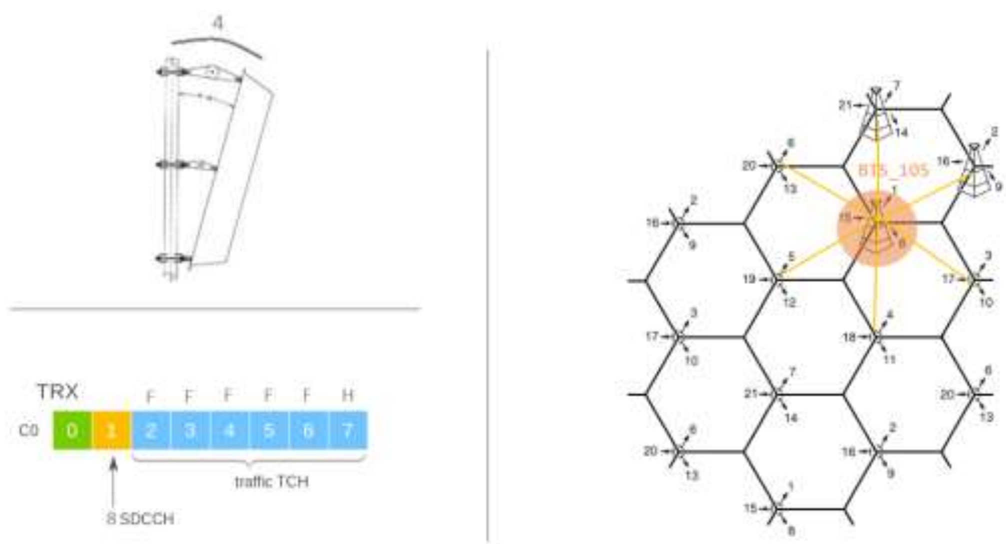


FIGURE 9.1: VISUALIZATION OF CURRENT PARAMETERS OF BTS_105

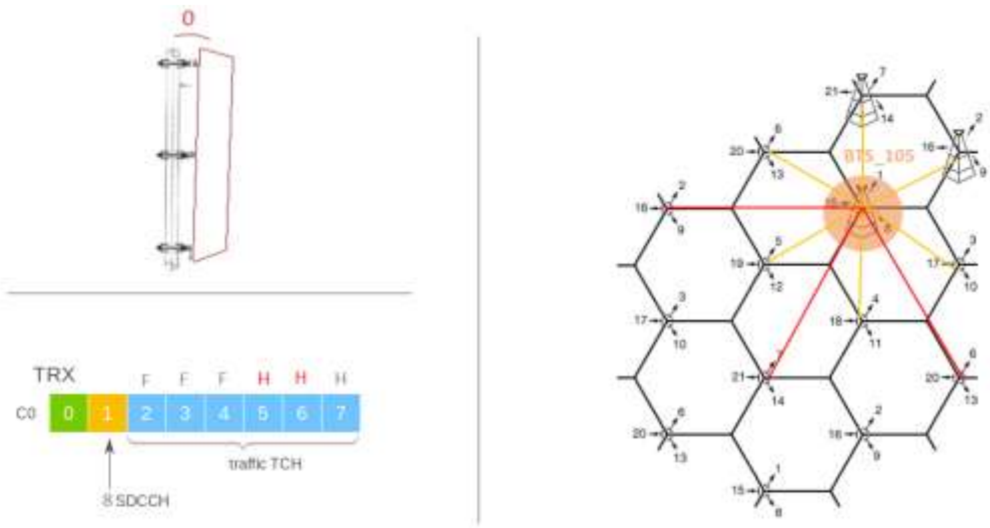


FIGURE 9.2: VISUALIZATION OF NEW PARAMETERS OF BTS_105

- For BTS_138: Change the RBS type from 3 to 2 and lower the antenna tile to be 0 or increase the height of the tower.

TABLE 9.2: TUNING PARAMETERS DATA OF THE REFERENCE SET OF BTS_138

Index	No. Frequencies	No. Neighbors	Site Category	RBS Type	Technology	Antenna Type	Antenna. Tilt	Height	DTHAMR	DTHNAMR
BTS_138	78	69	1	3	3	5	2	21	46	21
BTS_286	48	27	1	3	1	1	4	34	60	38
BTS_304	82	87	1	2	3	5	2	26.5	56	56
BTS_313	86	81	1	2	3	5	6	40	10	10

- For BTS_19: The antenna type of should be changed from 4 to 5, and it should define more neighbors to the site from 53 to something in the 70s. Another recommendation is to decrease the DTHAMR parameter to 56.

TABLE 9.3: TUNING PARAMETERS DATA OF THE REFERENCE SET OF BTS_19

Index	No. Frequencies	No. Neighbors	Site Category	RBS Type	Technology	Antenna Type	Antenna. Tilt	Height	DTHAMR	DTHNAMR
BTS_19	76	53	1	2	4	0	22	70	56	4
BTS_304	82	87	1	2	5	2	26.5	56	56	5
BTS_313	86	81	1	2	5	6	40	10	10	5

- For BTS_71: The category of the site should be changed from 2 to 1, and either way, to change DTHAMR or DTHNAMR to be match either 15s or 45s.

TABLE 9.4: TUNING PARAMETERS DATA OF THE REFERENCE SET OF BTS_71

Index	No. Frequencies	No. Neighbors	Site Category	RBS Type	Technology	Antenna Type	Antenna. Tilt	Height	DTHAMR	DTHNAMR
BTS_71	70	39	2	2	3	5	2	21.5	45	15
BTS_38	90	72	1	2	3	4	2	26	76	76
BTS_222	76	73	1	2	3	5	0	23.5	45	45
BTS_282	58	33	1	1	1	7	0	28	80	80
BTS_313	86	81	1	2	3	5	6	40	10	10

- For BTS_75: The category of the site should be changed from 2 to 1 and should match DTHAMR or DTHNAMR parameters. Additionally, the antenna tile should be lowered to 0, or the height of the tower should be increased.

TABLE 9.5: TUNING PARAMETERS DATA OF THE REFERENCE SET OF BTS_75

Index	No. Frequencies	No. Neighbors	Site Category	RBS Type	Technology	Antenna Type	Antenna. Tilt	Height	DTHAMR	DTHNAMR
BTS_75	76	43	2	2	3	5	2	22	45	15
BTS_222	76	73	1	2	3	5	0	23.5	45	45
BTS_286	48	27	1	3	1	1	4	34	60	38
BTS_304	82	87	1	2	3	5	2	26.5	56	56
BTS_313	86	81	1	2	3	5	6	40	10	10

- For BTS_76: Both the number of frequencies and the neighbors should be increased as well as changing the category of the site to be 1 instead of 2.

TABLE 9.6: TUNING PARAMETERS DATA OF THE REFERENCE SET OF BTS_76

Index	No. Frequencies	No. Neighbors	Site Category	RBS Type	Technology	Antenna Type	Antenna. Tilt	Height	DTHAMR	DTHNAMR
BTS_76	68	48	2	2	3	5	2	23	45	15
BTS_304	82	87	1	2	3	5	2	26.5	56	56
BTS_313	86	81	1	2	3	5	6	40	10	10

- For BTS_77: The antenna tilt should be changed from 2 to 0, or the height of the tower should be increased to be at the end of 20s. Also, changing the category of the site from 2 to 1 is another recommendation besides changing the parameter DTHNAMR to be 45 instead of 15.

TABLE 9.7: TUNING PARAMETERS DATA OF THE REFERENCE SET OF BTS_77

Index	No. Frequencies	No. Neighbors	Site Category	RBS Type	Technology	Antenna Type	Antenna. Tilt	Height	DTHAMR	DTHNAMR
BTS_77	74	54	2	2	3	5	2	21	45	15
BTS_222	76	73	1	2	3	5	0	23.5	45	45
BTS_286	48	27	1	3	1	1	4	34	60	38
BTS_304	82	87	1	2	3	5	2	26.5	56	56
BTS_313	86	81	1	2	3	5	6	40	10	10

9.2 Opportunities to Improve the Network

As I conclude my recommendations, I would like to highlight some other insights that might help the radio optimization engineer to improve the efficiency of the overall network, which are:

- Across the five models, 7 BTSs are in the high opportunity group.
- The super-efficiency scores show that branch BTS_285 is the most efficient branch, but it is not on the reference set of the high Opportunity group.
- BTS_290 is the only one that is efficient across the five models, and it has a super efficiency of 1.

- Changes in the parameters will be based on the best practices of the peers.
- Check the insights from the discussion section about the analysis of the tuning parameters to make some changes, for instance, replace the RBS 2.
- The general idea of the network in this area:
  - It is good in accessibility, service integrity, mobility, and retainability.
  - The speech quality and the ability to move successfully are close to each between the BTSs.

TABLE 9.8: OVERALL NETWORK EFFICIENCY RESULTS

Model	No. of efficient BTS	Average of efficiency	Std.dev.
General	19	0.5169	0.2146
Accessibility	8	0.4235	0.2032
Retainability	7	0.3928	0.21
Mobility	5	0.3985	0.1881
Service Integrity	5	0.4147	0.1827

Chapter 10 Conclusion

Mobile telecom technology has grown over the past several years, and cellular providers are trying to provide the proper services by adopting new technologies while minimizing the cost of the resources. However, cellular providers must maximize the efficiency of mobile infrastructures. In this study, we analyzed the data of 434 BTSs of a local provider in North Africa using the Data Envelopment Analysis method. This study provides an initial model to evaluate the mobile BTSs regarding multi-input and multi-outputs that would be useful for radio network optimization engineers to have an umbrella of KPIs to benchmark the stations' efficiency. The primary objective of this study is to develop a set of references for inefficient BTSs based on best practice BTSs. This model will help operators to enhance the inefficient BTSs by highlighting the changes from the practices, and by spending more effort on this gap to achieve the industry regulatory service and global KPIs standard.

10.1 Contributions

While the individual KPIs provide sufficient insights to the degree of use of accessibility radio indicators, this analysis suggests detailed information of the relative BTSs performance, which leads to a high level of insight for network performance improvements. Even though there are many methods for enhancing the parameter configurations for the BTSs, there is a lack of comprehensive tools.

I believe this research will deliver an inclusive model for tuning the BTS's parameters, and for providing insights for a better configuration of inefficient BTSs based on the best practice of efficient BTSs. The models will include the reference set, which offers improvements opportunities that the network engineers can use. Overall, I believe this research will maximize customer satisfaction for the cellular providers and add value in the following:

- Create a better understanding of the dynamics surrounding mobile telecom infrastructure decision making, in general, and mobile base stations in particular.
- The research can increase cellular network efficiency by determining the inefficient BTS, and evaluate their performance based on multiple KPIs and offer suggestions for better practices.
- The research can suggest enhancements to the BTSs to maximize the efficiency of the inefficient BTSs based on related best practices BTSs. This guides the operators to spend more effort and time on high potential improvement areas.
- The methodology assists decision-makers, and more specifically, the radio network optimization engineers, with its overall network services and compares the network performance to its competitors.

- The benchmarking process will be used as a tool to check customer satisfaction and is an improved approach for cellular network performance.
- The managerial team can differentiate between the quality of equipment and vendors by defining BTS productivity and efficiency using this model.
- Provide a decision-making tool that will help the management team and mobile providers improve the cellular infrastructure, and to get an efficient cellular system for handling competitor market requirements.
- Using the Lambda table to provide recommendations to improve the inefficient units.
- Evaluate performance based on multiple KPIs and get suggestions for better practices.
- Give guidelines for network optimization engineers to improve the inefficient BTSs.
- Check customer satisfaction and provide recommendations to maximize it.
- Differentiate between the quality of equipment and vendors.
- Lead to developing a standard global mobile network KPI that indicates an ordinary cell or BTS efficiency.

10.2 Implications

10.2.1 Importance of the BTS

Providers mostly focus on three main elements including coverage, capacity, and quality of service (Alam 2013). All three are direct to the BTS. The BTS controls the radio interface to the Mobile Station (MS). In the cellular network, the BTS is considered to be one of the critical infrastructures (Alenoghena *et al.* 2016), and is directly related to the cost of the network (Song and Kim 2001, Prasad and Sridhar 2008, Awad *et al.* 2015). Therefore, the best way to reach the desired results is to focus on the BTS. There are many studies on productivity and efficiency measurement of the BTS even in the early stages of cellular planning. Some studies addressed the concern for the optimal placement of BTS, and the needs and significance of studying the efficiency of the BTSs (Alenoghena *et al.* 2016). Thus, the critical point of maintaining customer satisfaction is mastering resource management and obtaining efficient BTSs. Cellular providers use QoS reports for each BTS to detect the service quality of the area, and to determine if the individual network elements or services are performing overall QoS (Kyriazakos *et al.* 2002, Haider *et al.* 2009, Alam 2013). With the explosive growth in the number of subscribers, and the technology changes that mobile telecom has witnessed, providers should provide an extended network of efficient BTSs to meet the traffic demands of the subscribers.

10.2.2 Importance of KPIs and QoS

In general, service is defined as a set of benefits that are delivered from a provider to consumers (Hung *et al.* 2003, Adekitan 2014). The QoS in cellular networks is the capability of the network to provide a satisfactory level of service to the subscribers and is measured by several KPIs that give a more meaningful measurement of performance (Mojisola and Gbolahan 2015). Recently, a great deal of attention has been given to evaluation of the QoS and optimization of the operation of cellular networks using standard KPIs since they can be used to judge the QoS and the mobile network performance (Otero *et al.* 2010, Awada *et al.* 2011, Kadioğlu *et al.* 2015, Osunade and Oyesanya 2016, Galadanci and Abdullahi 2018). Cellular quality services have been a major concern worldwide in the telecommunications industry (Adekitan 2014). A study by Mojisola and Gbolahan summarized the purpose of measuring QoS in the mobile network to help enhance the existing capacity and coverage of the network, which ensures delivery service quality that fulfills the customer demands (Mojisola and Gbolahan 2015). Tools for monitoring the networking performance assist in testing the network equipment manufacturers. Therefore, there is a strong relationship between service quality and subscriber satisfaction (Adekitan 2014), and perceived service quality is a component of customer satisfaction (Zeithaml *et al.* 1996). Additionally, many studies pointed out that the higher the ability to provide better services for mobile providers, the higher the potential to attract more customers and assure customer satisfaction (Mojisola and Gbolahan 2015).

The KPIs provide significant information about the subscribers, assess the state of the business, and assist in prescribing a progression of performance. However, these individual KPIs only allow the assessment of efficiency of the BTSs on one dimension and identifying the other areas would be advisable. The need to think in different ways to optimize the mobile network performance has to be clearly explained to the managerial teams. Using a robust and objective management tool for benchmarking mobile BTSs efficiency with the vital radio Key Performance Indicators (KPIs) for evaluating the technical efficiency of the mobile BTSs is critical. A study by Kadioğlu, Dalveren, and Kara provided a methodology that can be used to benchmark cellular network operators using KPIs (Kadioğlu *et al.* 2015). They used a simple ratio to calculate six main performance indicators. This traditional methodology did not consider the number of resources that were available for each unit, which can have a significant impact. Therefore, using the DEA, this limitation can be handled since the input factors will be included in the calculations, which will give more robust results.

10.3 Limitation and Future Work

Over the years, various works have applied data mining approaches in the mobile telecom industry. One example is integrating churn management, which is the ability of the mobile provider to control the customer movement from one provider to another by forecasting the customer decisions using three data mining techniques: K-means cluster, decision tree, and neural network techniques (Larivière and Van den Poel 2004, Hung *et al.* 2006). Another study noted that data mining implementation in telecom is used to find an associated rule of call waiting and display (Fu 1997), and to indicate the efficiency of the telephone installation in the market (Lemos *et al.* 2005). I can incorporate data mining techniques to retain existing customers and attract new customers through call analysis and customer loyalty.

In this report, the developed methodology is applied to two stages using a sample of data to illustrate the proposed approach. However, I might integrate other methods to help develop my model to solve a complicated situation and problem. For instance, using the TOPSIS for a better and unique ranking scheme may be relevant. This approach was used in a study to improve the discrimination power of DEA analysis and to handle negative data (Chitnis and Vaidya 2016). Thus, I can use the HDM or other weighting methods to determine the weights if practitioners decide to give the inputs and outputs different priorities. This is based on top management's priorities as well as the primary objective.

Additionally, the FCM could be integrated with DEA to help understand the influence between the inputs or outputs. This makes the recommendation more valuable and assesses the robustness of improving the inefficient BTS. Defining the threshold lines in the performance matrix was taken without a study or a strong reason, which makes the results less robust. This needs more study in the future to enhance results and suggestions and to improve the operational efficiency of the inefficient units. Finally, the research's results can be validated by implementing the recommendations to the inefficient BTSs based on the settings of the BTSs in the reference set, and then later check the new data for the desired improvement in the efficiency of the inefficient BTSs.

With this exploratory model, we will be able to assess the complexity of the problem and extend the work to include other perspectives to achieve a more comprehensive model. Future research could use more data, and could expand the number of BTSs or, in the level of the cells, (Dabab and Anderson 2018) make the evaluation framework more robust. Also, we could analyze all networks, which would help to compare different vendors and BTS models. This initial model is focused on 2G technology, but this can be extended to include the newly available and coming technologies, and to use the benchmarking results when added the new technology to the site to measure the differences. Additionally, the bad outputs (KPIs) will be considered in the next research such as TCH Drop, which will make the results more clear. Finally, this work might lead to the development of a standard global mobile network KPI that indicates an ordinary cell or BTS efficiency, which will allow vendors and operators to determine the BTS status.

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Appendixes

Appendix A: The R Code

The libraries that are used

```
library(float)
library(knitr)
library(kableExtra)
library("pander", quietly=TRUE)
library(lpSolveAPI)
library(DJL)
library(MultiplierDEA)
library(dplyr)
library(pastecs)
library(ggplot2)
library(plotly)
library(TRA)
library(ggcorrplot)
```

Analysis

Loading the data in R environment

```
Data <- read.csv("All_Data_Factored_Final_Final.csv", header = TRUE)

Data_0 <- Data[,-c(11:12)]
Data_1 <- Data_0[, -c(12:21)]
Data_2 <- Data_0[, -c(2:11)]

pander(head(Data_1), caption="Sample Data of the BTS of Building the Models")
pander(head(Data_2), caption="Sample Data of the BTS of Tuning the Parameters")

# Showing descriptive statistics of the data

Data_desc_stat <- stat.desc(Data_1, basic=F)

pander(head(Data_desc_stat), caption="Basic descriptive statistics of the data")
```

General Model (GM)

```
### Drawing the diagram

XFigNames <- c("R1 (TCH_NO)", "R1 (SDCCH_NO)")
YFigNames <- c("KPI1 (TCH_T)", "KPI2 (SDCCH_T)",
          "KPI3 (TCH_SUC)", "KPI4 (SDCCH_SUC)",
          "KPI5 (RACH_SUC)", "KPI6 (HO_SUC)",
          "KPI7 (SQI_G)")

Figure_GM<-DrawIOdiagram(XFigNames,YFigNames,
                '"\n\n\n\n\nDEA\nGeneral\nModel\n\n\n\n\n "' )
Figure_GM

### model

x <- Data_1 %>% select(TCH_NO, SDCCH_NO)
 row.names(x)<-Data_1[,1]

y_G <- Data_1 %>% select(TCH_T, SDCCH_T, TCH_SUCC, SDCCH_SUC, RACH_SUC, HO_S
UC, SQI_G)
 row.names(y_G)<-Data_1[,1]



### VRS-OUTPUT results

DEA_VRE_OUT_GM <- dm.dea(x, y_G, rts="vrs", orientation="o")
BTS_Efficiency_GM <- (1/DEA_VRE_OUT_GM$eff)

Results_DEA_GM <- data.frame(Data_1$Index , BTS_Efficiency_GM)
pander(head(Results_DEA_GM), caption="VRS-OUTPUT Efficiency Sample Results")



### Drawing the results graphically

plot_ly(Results_DEA_GM, x=~ BTS_Efficiency_GM, type="histogram")



### Super efficiency VRS-OUTPUT-S results

DEA_Super_OUT_VRS_GM <- dm.dea(x, y_G, rts="vrs", orientation="o", se=TRUE)
Result_Supr_GM <- data.frame (sort(1/DEA_Super_OUT_VRS_GM$eff, decreasing = TR
UE))
```

```
colnames(Result_Supr_GM) <- c("BTS_Super_Efficiency_GM")
pander(head(Result_Supr_GM), caption="BTS's Super Efficiency Sample Results")

#### Drawing the results graphicaly

plot_ly(Result_Supr_GM, x=~ BTS_Super_Efficiency_GM, type="histogram")

All_Results_DEA_GM <- data.frame(Data_1$Index, BTS_Efficiency_GM, (1/DEA_Super_
OUT_VRS_GM$eff))
colnames(All_Results_DEA_GM) <- c("BTS", "BTS_Efficiency_GM", "BTS_Super_Efficienc
y_GM")
Results_DEA_Print_GM <-dplyr::filter(All_Results_DEA_GM, BTS_Super_Efficiency_GM
>=1)



### Drawing the performance matrix

All_Results_DEA_GM <- dplyr::mutate(All_Results_DEA_GM,BTS_Revenue= Data_1$Rev
enue)

plot_ly(All_Results_DEA_GM, x= ~ BTS_Revenue, y= ~ BTS_Efficiency_GM, type="scatter
",mode = "markers")%>%

 add_markers(marker=list( size=ifelse(All_Results_DEA_GM$BTS_Revenue >550,10,5),
opacity=0.9, color=ifelse(All_Results_DEA_GM$BTS_Efficiency_GM>0.7,"blue","red")),
        showlegend = FALSE)%>%

 add_lines(x = c(550, 550), y = c(0, 1), name = "Revenue Threshold") %>%
 add_lines(x = c(0, 700), y = c(0.7, 0.7), name = "Efficiency Threshold")%>%
 layout(showlegend = FALSE)



#### Dividing the DMUs to groups

Category_1_GM <- dplyr::filter(All_Results_DEA_GM, BTS_Revenue >550, BTS_Efficienc
y_GM >0.7)
pander(head(Category_1_GM), caption="Category 1 of General Model (Optimal BTSs)")

Category_2_GM <-dplyr::filter(All_Results_DEA_GM, BTS_Revenue >550, BTS_Efficiency
_GM <0.7)
pander(head(Category_2_GM), caption="Category 2 of General Model (High Opportunit
y BTSs)")

Category_3_GM <-dplyr::filter(All_Results_DEA_GM, BTS_Revenue <550, BTS_Efficiency
```

```
_GM <0.7)
pander(head(Category_3_GM), caption="Category 3 of General Model (Medium Opport
unity BTSs)")

Category_4_GM <-dplyr::filter(All_Results_DEA_GM, BTS_Revenue <550, BTS_Efficiency
_GM >0.7)
pander(head(Category_4_GM), caption="Category 4 of General Model (Low Opportunit
y BTSs)")

BTS <- 434
BTSNAMES <- lapply(list(rep("BTS_", BTS)), paste0, 1:BTS)
All_BTSNAMES <- as.matrix(data.frame(BTSNAMES), ncol=1,nrow=434)
colnames(All_BTSNAMES) <- "BTS"

GM_DEA_mult<-DeaMultiplierModel(x,y_G,rts = "vrs", orientation="output")

Lambda_data_GM <- as.matrix(GM_DEA_mult$Lambda)
Final_Lambda_Data_GM_G2 <- matrix(c(Lambda_data_GM), ncol=434,nrow=434, dimn
ames = c(BTSNAMES, BTSNAMES))

Results_GM_G2_3 <- (poscol((Final_Lambda_Data_GM_G2)))
Results_GM_G2_4 <- cbind(All_BTSNAMES, Results_GM_G2_3)
Results_GM_G2_5 <- merge(Category_2_GM, Results_GM_G2_4, by.x = "BTS", by.y = "B
TS", all.x=TRUE)

Clean1 <- Results_GM_G2_5 [,-3]

Clean11 <- data.frame (Clean1)
Clean2 <- data.matrix (Clean11)
Final_Table_GM_G2 <- poscol(cbind(Clean2))

panderOptions('table.continues', '')
pander((Clean1), caption="Sample of Final Results of Category 2 for General Model with
the Reference Set")
```

Accessibility Model (AM)

```
### Drawing the diagram

XFigNames <- c("R1 (TCH_NO)", "R1 (SDCCH_NO)")
YFigNames <- c("KPI1 (TCH_T)", "KPI2 (SDCCH_T)",
          "KPI3 (TCH_SUC)", "KPI4 (SDCCH_SUC)",
          "KPI5 (RACH_SUC)")
```

```
Figure_AM<-DrawIOdiagram(XFigNames,YFigNames,
                    '"\n\n\nDEA\nGeneral\nAccess\n\n\n"' )
Figure_AM



## Analysis

x <- Data_1 %>% select(TCH_NO, SDCCH_NO)
 row.names(x)<-Data_1[,1]

y_A <- Data_1 %>% select(TCH_T, SDCCH_T, TCH_SUCC, SDCCH_SUC, RACH_SUC)
 row.names(y_A)<-Data_1[,1]



### VRS-OUTPUT results

DEA_VRE_OUT_AM <- dm.dea(x, y_A, rts="vrs", orientation="o")
BTS_Efficiency_AM <- (1/DEA_VRE_OUT_AM$eff)

Results_DEA_AM <- data.frame(Data_1$Index , BTS_Efficiency_AM)
pander(head(Results_DEA_AM), caption="VRS-OUTPUT Efficiency Sample Results")



### Drawing the results graphically

plot_ly(Results_DEA_AM, x=~ BTS_Efficiency_AM, type="histogram")



### Super efficiency VRS-OUTPUT-S results

DEA_Super_OUT_VRS_AM <- dm.dea(x, y_A, rts="vrs", orientation="o", se=TRUE)
Result_Supr_AM <- data.frame (sort(1/DEA_Super_OUT_VRS_AM$eff, decreasing = TR
UE))
colnames(Result_Supr_AM) <- c("BTS_Super_Efficiency_AM")
pander(head(Result_Supr_AM), caption="BTS's Super Efficiency Sample Results")



### Drawing the results graphically

plot_ly(Result_Supr_AM, x=~ BTS_Super_Efficiency_AM, type="histogram")
```

```
All_Results_DEA_AM <- data.frame(Data_1$Index, BTS_Efficiency_AM, (1/DEA_Super_
OUT_VRS_AM$eff))
colnames(All_Results_DEA_AM) <- c("BTS", "BTS_Efficiency_AM", "BTS_Super_Efficienc
y_AM")
Results_DEA_Print_AM <-dplyr::filter(All_Results_DEA_AM, BTS_Super_Efficiency_AM >
=1)
pander(head(Results_DEA_Print_AM), caption="BTS's Efficiency Sample results")



### Drawing the performance matrix

All_Results_DEA_AM <- dplyr::mutate(All_Results_DEA_AM,BTS_Revenue= Data_1$Rev
enue)

plot_ly(All_Results_DEA_AM, x= ~ BTS_Revenue, y= ~ BTS_Efficiency_AM, type="scatter
",mode = "markers")%>%

  add_markers(marker=list( size=ifelse(All_Results_DEA_AM$BTS_Revenue >550,10,5),
opacity=0.9, color=ifelse(All_Results_DEA_AM$BTS_Efficiency_AM>0.7,"blue","red")),
           showlegend = FALSE)%>%

  add_lines(x = c(550, 550), y = c(0, 1), name = "Revenue Threshold") %>%
  add_lines(x = c(0, 700), y = c(0.7, 0.7), name = "Efficiency Threshold")%>%
  layout(showlegend = FALSE)



### Dividing the DMUs to groups

Category_1_AM <- dplyr::filter(All_Results_DEA_AM, BTS_Revenue >550, BTS_Efficiency
_AM >0.7)
pander(head(Category_1_AM), caption="Category 1 of Access Model (Optimal BTSs)")

Category_2_AM <-dplyr::filter(All_Results_DEA_AM, BTS_Revenue >550, BTS_Efficiency
_AM <0.7)
pander(head(Category_2_AM), caption="Category 2 of Access Model (High Opportunity
BTSs)")

Category_3_AM <-dplyr::filter(All_Results_DEA_AM, BTS_Revenue <550, BTS_Efficiency
_AM <0.7)
pander(head(Category_3_AM), caption="Category 3 of Access Model (Medium Opportu
nity BTSs)")

Category_4_AM <-dplyr::filter(All_Results_DEA_AM, BTS_Revenue <550, BTS_Efficiency
_AM >0.7)
```

```
pander(head(Category_4_AM), caption="Category 4 of Access Model (Low Opportunity
BTSs)")

AM_DEA_mult<-DeaMultiplierModel(x,y_A,rts = "vrs", orientation="output")
Lambda_data_AM <- as.matrix(AM_DEA_mult$Lambda)
Final_Lambda_Data_AM_G2 <- matrix(c(Lambda_data_AM), ncol=434,nrow=434, dimn
ames = c(BTSNAMES, BTSNAMES))

Results_AM_G2_3 <- poscol(cbind(Final_Lambda_Data_AM_G2))
Results_AM_G2_4 <- cbind(All_BTSNAMES, Results_AM_G2_3)
Results_AM_G2_5 <- merge(Category_2_AM, Results_AM_G2_4, by.x = "BTS", by.y = "B
TS", all.x=TRUE)

Final_Table_AM_G2 <- Results_AM_G2_5 [,-3]
pander(head(Final_Table_AM_G2), caption="Sample of Final Results of Category 2 for A
ccess Model with the Reference Set")
```

Retainability Model (RM)

```
### Drawing the diagram

XFigNames <- c("R1 (TCH_NO)", "R1 (SDCCH_NO)")
YFigNames <- c("KPI3 (TCH_SUC)", "KPI4 (SDCCH_SUC)")

Figure_RM<-DrawIOdiagram(XFigNames,YFigNames,
                '"\n\nDEA\nRetain\nModel\n "' )
Figure_RM



### Analysing


x <- Data_1 %>% select(TCH_NO, SDCCH_NO)
  row.names(x)<-Data_1[,1]

y_R <- Data_1 %>% select(TCH_SUCC, SDCCH_SUC)
  row.names(y_R)<-Data_1[,1]



### VRS-OUTPUT results
```

```
DEA_VRE_OUT_RM <- dm.dea(x, y_R, rts="vrs", orientation="o")
BTS_Efficiency_RM <- (1/DEA_VRE_OUT_RM$eff)

Results_DEA_RM <- data.frame(Data_1$Index , BTS_Efficiency_RM)
pander(head(Results_DEA_RM), caption="VRS-OUTPUT Efficiency Sample Results")



### Drawing the results graphically

plot_ly(Results_DEA_RM, x=~ BTS_Efficiency_RM, type="histogram")




### Super efficiency VRS-OUTPUT-S results

DEA_Super_OUT_VRS_RM <- dm.dea(x, y_R, rts="vrs", orientation="o", se=TRUE)
Result_Supr_RM <- data.frame (sort(1/DEA_Super_OUT_VRS_RM$eff, decreasing = TRU
E))
colnames(Result_Supr_RM) <- c("BTS_Super_Efficiency_RM")
pander(head(Result_Supr_RM), caption="BTS's Super Efficiency Sample Results")



### Drawing the results graphically

plot_ly(Result_Supr_RM, x=~ BTS_Super_Efficiency_RM, type="histogram")

All_Results_DEA_RM <- data.frame(Data_1$Index, BTS_Efficiency_RM, (1/DEA_Super_
OUT_VRS_RM$eff))
colnames(All_Results_DEA_RM) <- c("BTS", "BTS_Efficiency_RM", "BTS_Super_Efficiency
_RM")
Results_DEA_Print_RM <-dplyr::filter(All_Results_DEA_RM, BTS_Super_Efficiency_RM >
=1)
pander(head(All_Results_DEA_RM), caption="BTS's Efficiency Sample results")



### Drawing the performance matrix

All_Results_DEA_RM <- dplyr::mutate(All_Results_DEA_RM,BTS_Revenue= Data_1$Rev
enue)

plot_ly(All_Results_DEA_RM, x= ~ BTS_Revenue, y= ~ BTS_Efficiency_RM, type="scatter
",mode = "markers")%>%
```

```
 add_markers(marker=list( size=ifelse(All_Results_DEA_RM$BTS_Revenue >550,10,5),
opacity=0.9, color=ifelse(All_Results_DEA_RM$BTS_Efficiency_RM>0.7,"blue","red")),
          showlegend = FALSE)%>%

 add_lines(x = c(550, 550), y = c(0, 1), name = "Revenue Threshold") %>%
 add_lines(x = c(0, 700), y = c(0.7, 0.7), name = "Efficiency Threshold")%>%
 layout(showlegend = FALSE)



### Dividing the DMUs to groups

Category_1_RM <- dplyr::filter(All_Results_DEA_RM, BTS_Revenue >550, BTS_Efficiency
_RM >0.7)
pander(head(Category_1_RM), caption="Category 1 of Retain Model (Optimal BTSs)")

Category_2_RM <-dplyr::filter(All_Results_DEA_RM, BTS_Revenue >550, BTS_Efficiency
_RM <0.7)
pander(head(Category_2_RM), caption="Category 2 of Retain Model (High Opportunity
BTSs)")

Category_3_RM <-dplyr::filter(All_Results_DEA_RM, BTS_Revenue <550, BTS_Efficiency
_RM <0.7)
pander(head(Category_3_RM), caption="Category 3 of Retain Model (Medium Opportu
nity BTSs)")

Category_4_RM <-dplyr::filter(All_Results_DEA_RM, BTS_Revenue <550, BTS_Efficiency
_RM >0.7)
pander(head(Category_4_RM), caption="Category 4 of Retain Model (Low Opportunity
BTSs)")

RM_DEA_mult<-DeaMultiplierModel(x,y_R,rts = "vrs", orientation="output")
Lambda_data_RM <- as.matrix(RM_DEA_mult$Lambda)
Final_Lambda_Data_RM_G2 <- matrix(c(Lambda_data_RM), ncol=434,nrow=434, dimna
mes = c(BTSNAMES, BTSNAMES))



Results_RM_G2_3 <- poscol(cbind(Final_Lambda_Data_RM_G2))
Results_RM_G2_4 <- cbind(All_BTSNAMES, Results_RM_G2_3)
Results_RM_G2_5 <- merge(Category_2_RM, Results_RM_G2_4, by.x = "BTS", by.y = "B
TS", all.x=TRUE)

Final_Table_RM_G2 <- Results_RM_G2_5 [,-3]
pander(head(Final_Table_RM_G2), caption="Sample of Final Results of Category 2 for G
eneral Model with the Reference Set")
```

Mobility Model (MM)

```
### Drawing the diagram

XFigNames <- c("R1 (TCH_NO)", "R1 (SDCCH_NO)")
YFigNames <- c("KPI6 (HO_SUC)")

Figure_MM<-DrawIOdiagram(XFigNames,YFigNames,
                  '"\nDEA\nGeneral\nModel\n\n"' )
Figure_MM




### Analysing

x <- Data_1 %>% select(TCH_NO, SDCCH_NO)
 row.names(x)<-Data_1[,1]

y_M <- Data_1 %>% select(HO_SUC)
 row.names(y_M)<-Data_1[,1]



### VRS-OUTPUT results

DEA_VRE_OUT_MM <- dm.dea(x, y_M, rts="vrs", orientation="o")
BTS_Efficiency_MM <- (1/DEA_VRE_OUT_MM$eff)

Results_DEA_MM <- data.frame(Data_1$Index , BTS_Efficiency_MM)
pander(head(Results_DEA_MM), caption="VRS-OUTPUT Efficiency Sample Results")



### Drawing the results graphically

plot_ly(Results_DEA_MM, x=~ BTS_Efficiency_MM, type="histogram")
```

```
### Super efficiency VRS-OUTPUT-S results

DEA_Super_OUT_VRS_MM <- dm.dea(x, y_M, rts="vrs", orientation="o", se=TRUE)
Result_Supr_MM <- data.frame (sort(1/DEA_Super_OUT_VRS_MM$eff, decreasing = TR
UE))
colnames(Result_Supr_MM) <- c("BTS_Super_Efficiency_MM")
pander(head(Result_Supr_MM), caption="BTS's Super Efficiency Sample Results")



### Drawing the results graphically

plot_ly(Result_Supr_MM, x=~ BTS_Super_Efficiency_MM, type="histogram")

All_Results_DEA_MM <- data.frame(Data_1$Index, BTS_Efficiency_MM, (1/DEA_Super_
OUT_VRS_MM$eff))
colnames(All_Results_DEA_MM) <- c("BTS", "BTS_Efficiency_MM", "BTS_Super_Efficien
cy_MM")
Results_DEA_Print_MM <-dplyr::filter(All_Results_DEA_MM, BTS_Super_Efficiency_MM
>=1)
pander(head(Results_DEA_Print_MM), caption="BTS's Efficiency Sample results")



### Drawing the performance matrix

All_Results_DEA_MM <- dplyr::mutate(All_Results_DEA_MM,BTS_Revenue= Data_1$Re
venue)

plot_ly(All_Results_DEA_MM, x= ~ BTS_Revenue, y= ~ BTS_Efficiency_MM, type="scatt
er",mode = "markers")%>%

 add_markers(marker=list( size=ifelse(All_Results_DEA_MM$BTS_Revenue >550,10,5),
opacity=0.9, color=ifelse(All_Results_DEA_MM$BTS_Efficiency_MM>0.7,"blue","red")),
          showlegend = FALSE)%>%

 add_lines(x = c(550, 550), y = c(0, 1), name = "Revenue Threshold") %>%
 add_lines(x = c(0, 700), y = c(0.7, 0.7), name = "Efficiency Threshold")%>%
 layout(showlegend = FALSE)



### Dividing the DMUs to groups

Category_1_MM <- dplyr::filter(All_Results_DEA_MM, BTS_Revenue >550, BTS_Efficien
cy_MM >0.7)
pander(head(Category_1_MM), caption="Category 1 of Mobility Model (Optimal BTSs)"
```

```
)

Category_2_MM <-dplyr::filter(All_Results_DEA_MM, BTS_Revenue >550, BTS_Efficienc
y_MM <0.7)
pander(head(Category_2_MM), caption="Category 2 of Mobility Model (High Opportuni
ty BTSs)")

Category_3_MM <-dplyr::filter(All_Results_DEA_MM, BTS_Revenue <550, BTS_Efficienc
y_MM <0.7)
pander(head(Category_3_MM), caption="Category 3 of Mobility Model (Medium Oppor
tunity BTSs)")

Category_4_MM <-dplyr::filter(All_Results_DEA_MM, BTS_Revenue <550, BTS_Efficienc
y_MM >0.7)
pander(head(Category_4_MM), caption="Category 4 of Mobility Model (Low Opportuni
ty BTSs)")

MM_DEA_mult<-DeaMultiplierModel(x,y_M,rts = "vrs", orientation="output")
Lambda_data_MM <- as.matrix(MM_DEA_mult$Lambda)
Final_Lambda_Data_MM_G2 <- matrix(c(Lambda_data_MM), ncol=434,nrow=434, dim
names = c(BTSNAMES, BTSNAMES))


Results_MM_G2_3 <- poscol(cbind(Final_Lambda_Data_MM_G2))
Results_MM_G2_4 <- cbind(All_BTSNAMES, Results_MM_G2_3)
Results_MM_G2_5 <- merge(Category_2_MM, Results_MM_G2_4, by.x = "BTS", by.y = "
BTS", all.x=TRUE)

Final_Table_MM_G2 <- Results_MM_G2_5 [,-3]
pander(head(Final_Table_MM_G2), caption="Sample of Final Results of Category 2 for
General Model with the Reference Set")
```

Service Integrity Model (SIM)

```
### Drawing the diagram

XFigNames <- c("R1 (TCH_NO)", "R1 (SDCCH_NO)")
YFigNames <- c("KPI7 (SQI_G)")

Figure_SIM<-DrawIOdiagram(XFigNames,YFigNames,
```

```
                    '"\nDEA\nService Integrity\nModel\n "' )
Figure_SIM


### Analysis

x <- Data_1 %>% select(TCH_NO, SDCCH_NO)
 row.names(x)<-Data_1[,1]

y_S <- Data_1 %>% select(SQI_G)
 row.names(y_S)<-Data_1[,1]



### VRS-OUTPUT results

DEA_VRE_OUT_SIM <- dm.dea(x, y_S, rts="vrs", orientation="o")
BTS_Efficiency_SIM <- (1/DEA_VRE_OUT_SIM$eff)

Results_DEA_SIM <- data.frame(Data_1$Index , BTS_Efficiency_SIM)
pander(head(Results_DEA_SIM), caption="VRS-OUTPUT Efficiency Sample Results")



### Drawing the results graphically

plot_ly(Results_DEA_SIM, x=~ BTS_Efficiency_SIM, type="histogram")



### Super efficiency VRS-OUTPUT-S results

DEA_Super_OUT_VRS_SIM <- dm.dea(x, y_S, rts="vrs", orientation="o", se=TRUE)
Result_Supr_SIM <- data.frame (sort(1/DEA_Super_OUT_VRS_SIM$eff, decreasing = TR
UE))
colnames(Result_Supr_SIM) <- c("BTS_Super_Efficiency_SIM")
pander(head(Result_Supr_SIM), caption="BTS's Super Efficiency Sample Results")



### Drawing the results graphically

plot_ly(Result_Supr_SIM, x=~ BTS_Super_Efficiency_SIM, type="histogram")

All_Results_DEA_SIM <- data.frame(Data_1$Index, BTS_Efficiency_SIM, (1/DEA_Super_
OUT_VRS_SIM$eff))
colnames(All_Results_DEA_SIM) <- c("BTS", "BTS_Efficiency_SIM", "BTS_Super_Efficienc
```

```
y_SIM")
Results_DEA_Print_SIM <-dplyr::filter(All_Results_DEA_SIM, BTS_Super_Efficiency_SIM
>=1)
pander(head(Results_DEA_Print_SIM), caption="BTS's Efficiency Sample results")



### Drawing the performance matrix

All_Results_DEA_SIM <- dplyr::mutate(All_Results_DEA_SIM,BTS_Revenue= Data_1$Re
venue)

plot_ly(All_Results_DEA_SIM, x= ~ BTS_Revenue, y= ~ BTS_Efficiency_SIM, type="scatte
r",mode = "markers")%>%

 add_markers(marker=list( size=ifelse(All_Results_DEA_SIM$BTS_Revenue >550,10,5),
opacity=0.9, color=ifelse(All_Results_DEA_SIM$BTS_Efficiency_SIM>0.7,"blue","red")),
          showlegend = FALSE)%>%

 add_lines(x = c(550, 550), y = c(0, 1), name = "Revenue Threshold") %>%
 add_lines(x = c(0, 700), y = c(0.7, 0.7), name = "Efficiency Threshold")%>%
 layout(showlegend = FALSE)



### Dividing the DMUs to groups

Category_1_SIM <- dplyr::filter(All_Results_DEA_SIM, BTS_Revenue >550, BTS_Efficienc
y_SIM >0.7)
pander(head(Category_1_SIM), caption="Category 1 of Service Integrity Model (Optimal
BTSs)")

Category_2_SIM <-dplyr::filter(All_Results_DEA_SIM, BTS_Revenue >550, BTS_Efficiency
_SIM <0.7)
pander(head(Category_2_SIM), caption="Category 2 of Service Integrity Model (High Op
portunity BTSs)")

Category_3_SIM <-dplyr::filter(All_Results_DEA_SIM, BTS_Revenue <550, BTS_Efficiency
_SIM <0.7)
pander(head(Category_3_SIM), caption="Category 3 of Service Integrity Model (Mediu
m Opportunity BTSs)")

Category_4_SIM <-dplyr::filter(All_Results_DEA_SIM, BTS_Revenue <550, BTS_Efficiency
_SIM >0.7)
```

```
pander(head(Category_4_SIM), caption="Category 4 of Service Integrity Model (Low Op
portunity BTSs)")

SIM_DEA_mult<-DeaMultiplierModel(x,y_S,rts = "vrs", orientation="output")
Lambda_data_SIM <- as.matrix(SIM_DEA_mult$Lambda)
Final_Lambda_Data_SIM_G2 <- matrix(c(Lambda_data_SIM), ncol=434,nrow=434, dimn
ames = c(BTSNAMES, BTSNAMES))


Results_SIM_G2_3 <- poscol(cbind(Final_Lambda_Data_SIM_G2))
Results_SIM_G2_4 <- cbind(All_BTSNAMES, Results_SIM_G2_3)
Results_SIM_G2_5 <- merge(Category_2_SIM, Results_SIM_G2_4, by.x = "BTS", by.y = "
BTS", all.x=TRUE)

Final_Table_SIM_G2 <- Results_SIM_G2_5 [,-3]
pander(head(Final_Table_SIM_G2), caption="Sample of Final Results of Category 2 for G
eneral Model with the Reference Set")
```

Further Analysis of the General Model

```
RegData_1 <- cbind(Data_1, Results_DEA_GM)
RegData_2 <- RegData_1 [,-11][,-11] [,-1]

RegData_3 <- lm(data = RegData_2, BTS_Efficiency_GM~. )
summary(RegData_3)

ComData_2 <- cbind(Data_2, Results_DEA_GM)
New_ComData_2 <- ComData_2 [,-1] [,-11] [,-3] [,-3] [,-3] [,-3]

corr <- round(cor(New_ComData_2), 3)
ggcorrplot(corr, lab = TRUE, colors = c("#fc1442", "white","#1ad4af"))

plot_ly(data = ComData_2, y=~BTS_Efficiency_GM, x=~Antenna_Type, type = "box")

plot_ly(data = ComData_2, y=~BTS_Efficiency_GM, x=~Technology, type = "box")

plot_ly(data = ComData_2, y=~BTS_Efficiency_GM, x=~RBS_Type, type = "box")

plot_ly(data = ComData_2, y=~BTS_Efficiency_GM, x=~Site_Catogary, type = "box")
```

Recommendation Chapter

```
BTS_105 <- dplyr::filter(Data_2,Index=="BTS_105")
BTS_222 <- dplyr::filter(Data_2,Index=="BTS_222")
BTS_286 <- dplyr::filter(Data_2,Index=="BTS_286")
BTS_304 <- dplyr::filter(Data_2,Index=="BTS_304")
BTS_313 <- dplyr::filter(Data_2,Index=="BTS_313")
ComData_1 <- rbind(BTS_105, BTS_222, BTS_286, BTS_304, BTS_313)

pander(head(ComData_1), caption="Tuning Parameters Data of the Reference Set of BT
S_105")
```

For BTS_138

```
BTS_138 <- dplyr::filter(Data_2,Index=="BTS_138")
ComData_2 <- rbind(BTS_138, BTS_286, BTS_304, BTS_313)

pander(head(ComData_2), caption="Tuning Parameters Data of the Reference Set of BT
S_138")
```

For BTS_19

```
BTS_19 <- dplyr::filter(Data_2,Index=="BTS_19")
ComData_3 <- rbind(BTS_19, BTS_304, BTS_313)

pander(head(ComData_3), caption="Tuning Parameters Data of the Reference Set of BT
S_19")
```

For BTS_71

```
BTS_71 <- dplyr::filter(Data_2,Index=="BTS_71")
BTS_38 <- dplyr::filter(Data_2,Index=="BTS_38")
BTS_282 <- dplyr::filter(Data_2,Index=="BTS_282")

ComData_4 <- rbind(BTS_71, BTS_38, BTS_222, BTS_282, BTS_313)

pander(head(ComData_4), caption="Tuning Parameters Data of the Reference Set of BT
S_71")
```

For BTS_75

```
BTS_75 <- dplyr::filter(Data_2,Index=="BTS_75")
ComData_5 <- rbind(BTS_75, BTS_222, BTS_286, BTS_304, BTS_313)

pander(head(ComData_5), caption="Tuning Parameters Data of the Reference Set of BT
S_75")
```

BTS_76

```
BTS_76 <- dplyr::filter(Data_2,Index=="BTS_76")

ComData_6 <- rbind(BTS_76, BTS_304, BTS_313)

pander(head(ComData_6), caption="Tuning Parameters Data of the Reference Set of BT
S_76")
```

BTS_77

```
BTS_77 <- dplyr::filter(Data_2,Index=="BTS_77")
ComData_7 <- rbind(BTS_77,BTS_222, BTS_286, BTS_304, BTS_313)

pander(head(ComData_7), caption="Tuning Parameters Data of the Reference Set of BT
S_77")
```

Final Table of all models

```
xx1 <- mean(BTS_Efficiency_GM)
xx2 <- mean(BTS_Efficiency_AM)
xx3 <- mean(BTS_Efficiency_RM)
xx4 <- mean(BTS_Efficiency_MM)
xx5 <- mean(BTS_Efficiency_SIM)

zz1 <- sd(BTS_Efficiency_GM)
```

```
zz2 <- sd(BTS_Efficiency_AM)
zz3 <- sd(BTS_Efficiency_RM)
zz4 <- sd(BTS_Efficiency_MM)
zz5 <- sd(BTS_Efficiency_SIM)

yy1 <- length(which(BTS_Efficiency_GM == 1))
yy2 <- length(which(BTS_Efficiency_AM == 1))
yy3 <- length(which(BTS_Efficiency_RM == 1))
yy4 <- length(which(BTS_Efficiency_MM == 1))
yy5 <- length(which(BTS_Efficiency_SIM == 1))

X1 <- c("General", "Accessibility", "Retainability", "Mobility", "Service Integrity")
X2 <- c(19,8,7,5,5)
X3 <- c(xx1,xx2,xx3,xx4,xx5)
X4 <- c(zz1,zz2,zz3,zz4,zz5)

MM <- data.frame("Model" = X1, "No._of_efficient_BTS"=X2,  "Average_of_the_efficien
cy"=X3, "Std.dev."= X4)

pander(head(MM), caption="Overall Network Efficiency Results")
```

Appendix B: The All Results

Index	BTS Efficiency GM	BTS Efficiency AM	BTS Efficiency RM	BTS Efficiency MM	BTS Efficiency SIM
BTS_1	0.159	0.115	0.09576	0.03281	0.159
BTS_2	0.2184	0.2184	0.08637	0.01641	0.1019
BTS_3	0.5104	0.5104	0.5104	0.1895	0.3037
BTS_4	0.1845	0.1845	0.07752	0.009455	0.06626
BTS_5	0.3548	0.2871	0.232	0.08253	0.3548
BTS_6	0.421	0.3489	0.3437	0.101	0.421
BTS_7	0.7717	0.6835	0.6835	0.5621	0.7373
BTS_8	0.8538	0.8186	0.8186	0.7217	0.6248
BTS_9	0.9005	0.8419	0.8419	0.3398	0.9005
BTS_10	1	0.9465	0.9465	0.7148	0.7682
BTS_11	0.296	0.2727	0.2169	0.2886	0.2635
BTS_12	0.8092	0.7	0.7	0.7738	0.4917
BTS_13	0.3295	0.3295	0.3295	0.1851	0.3007
BTS_14	0.5439	0.5335	0.5335	0.3165	0.4985
BTS_15	0.7567	0.5744	0.5744	0.7267	0.5013
BTS_16	0.3661	0.3064	0.3064	0.3441	0.1728
BTS_17	0.6159	0.4934	0.4645	0.4527	0.4405
BTS_18	0.4687	0.3712	0.2906	0.4004	0.3837
BTS_19	0.6293	0.4798	0.4075	0.5145	0.5359
BTS_20	0.4531	0.4531	0.4531	0.2901	0.4384
BTS_21	0.5987	0.5179	0.4529	0.4533	0.5388
BTS_22	0.3451	0.1788	0.1554	0.3451	0.173
BTS_23	0.363	0.2791	0.2719	0.3201	0.2689
BTS_24	0.2617	0.2068	0.1773	0.203	0.2149
BTS_25	0.7685	0.6187	0.6187	0.5991	0.3834
BTS_26	0.4986	0.3461	0.2582	0.4622	0.3325

BTS_27	0.102	0.06392	0.05775	0.08704	0.06113
BTS_28	0.2959	0.2224	0.2181	0.227	0.2045
BTS_29	0.5648	0.4202	0.3938	0.4816	0.4687
BTS_30	0.3745	0.2838	0.2375	0.3065	0.2923
BTS_31	0.667	0.5066	0.3849	0.424	0.6662
BTS_32	1	0.9182	0.7383	0.7736	1
BTS_33	0.4955	0.4045	0.3847	0.3098	0.4755
BTS_34	0.3792	0.3027	0.2894	0.2706	0.2885
BTS_35	0.8408	0.8408	0.8308	0.3957	0.4719
BTS_36	1	1	1	0.6249	0.7183
BTS_37	0.5751	0.4333	0.3474	0.4683	0.4464
BTS_38	1	0.7001	0.7001	1	0.5583
BTS_39	0.3811	0.3244	0.3142	0.2258	0.3721
BTS_40	0.3817	0.3026	0.2168	0.2914	0.3375
BTS_41	0.4301	0.2873	0.2554	0.4063	0.2638
BTS_42	0.3249	0.3011	0.2497	0.2143	0.2904
BTS_43	0.3712	0.3125	0.2884	0.1729	0.3712
BTS_44	0.7725	0.6242	0.5497	0.2583	0.7725
BTS_45	0.807	0.6314	0.6314	0.6811	0.5389
BTS_46	0.588	0.5586	0.5586	0.4011	0.3031
BTS_47	0.7563	0.6278	0.5692	0.485	0.7196
BTS_48	0.3568	0.3038	0.286	0.2258	0.341
BTS_49	0.8225	0.7288	0.6318	0.5528	0.767
BTS_50	0.2736	0.2269	0.2238	0.1908	0.2514
BTS_51	0.5932	0.3977	0.3751	0.4833	0.3435
BTS_52	0.5929	0.5193	0.5193	0.5188	0.5021
BTS_53	0.7537	0.5425	0.3935	0.6589	0.6778
BTS_54	0.765	0.708	0.708	0.5827	0.5062
BTS_55	0.3229	0.2507	0.2114	0.2684	0.2624
BTS_56	0.5092	0.4258	0.3922	0.3924	0.4461
BTS_57	0.5135	0.4015	0.2483	0.3743	0.4652
BTS_58	0.2982	0.2203	0.2028	0.2474	0.2559
BTS_59	0.4324	0.3483	0.3184	0.3159	0.3901
BTS_60	0.5182	0.4229	0.3561	0.3918	0.4596
BTS_61	0.5599	0.4673	0.4104	0.3682	0.5281

BTS_62	0.7523	0.6807	0.6807	0.5412	0.5729
BTS_63	0.4498	0.354	0.354	0.4174	0.309
BTS_64	0.8336	0.6774	0.6774	0.7258	0.5768
BTS_65	0.323	0.2677	0.2677	0.283	0.2084
BTS_66	0.4715	0.376	0.3532	0.3826	0.4029
BTS_67	0.3456	0.2736	0.2371	0.2912	0.2889
BTS_68	0.5743	0.4024	0.3856	0.4641	0.378
BTS_69	0.544	0.4475	0.333	0.4569	0.4651
BTS_70	0.6668	0.3926	0.3814	0.6532	0.3991
BTS_71	0.6308	0.4317	0.371	0.5578	0.488
BTS_72	0.2184	0.1767	0.148	0.1872	0.1778
BTS_73	0.3463	0.283	0.2723	0.2736	0.2808
BTS_74	0.3087	0.2544	0.206	0.2508	0.257
BTS_75	0.5515	0.4331	0.4249	0.4241	0.4848
BTS_76	0.5253	0.3807	0.3063	0.4277	0.4483
BTS_77	0.6237	0.5122	0.4448	0.4983	0.5363
BTS_78	0.5805	0.5043	0.5043	0.4731	0.4591
BTS_79	0.4158	0.2541	0.2456	0.3523	0.2103
BTS_80	0.5525	0.5025	0.3675	0.4288	0.5495
BTS_81	0.4718	0.3288	0.2856	0.4207	0.3648
BTS_82	0.4914	0.4001	0.2975	0.3512	0.4484
BTS_83	0.4448	0.2974	0.2964	0.4202	0.2415
BTS_84	0.536	0.5135	0.5092	0.3228	0.4793
BTS_85	0.5522	0.4498	0.3449	0.327	0.5393
BTS_86	0.4916	0.4065	0.3296	0.3165	0.4671
BTS_87	0.4237	0.3842	0.3529	0.2414	0.4186
BTS_88	0.805	0.6017	0.6016	0.7035	0.5218
BTS_89	0.7324	0.7147	0.7147	0.4357	0.5932
BTS_90	0.1856	0.1492	0.136	0.1212	0.1755
BTS_91	0.689	0.5642	0.4854	0.4533	0.6497
BTS_92	0.4484	0.3624	0.3134	0.2586	0.4414
BTS_93	0.5581	0.4183	0.3994	0.4188	0.4057
BTS_94	0.4891	0.4149	0.3756	0.3078	0.4684
BTS_95	0.2409	0.1842	0.1778	0.2013	0.2024
BTS_96	0.2006	0.1591	0.1472	0.1663	0.1692

BTS_97	0.4897	0.412	0.412	0.3838	0.4253
BTS_98	0.7084	0.557	0.4782	0.6116	0.5966
BTS_99	0.4236	0.3203	0.2703	0.337	0.3663
BTS_100	0.4109	0.3278	0.2968	0.2725	0.3864
BTS_101	0.8473	0.4809	0.4809	0.8334	0.4428
BTS_102	0.2744	0.2063	0.1604	0.1958	0.2509
BTS_103	0.1841	0.1381	0.09368	0.1591	0.1484
BTS_104	0.2431	0.1885	0.1741	0.2102	0.1999
BTS_105	0.3422	0.2834	0.2578	0.2514	0.3077
BTS_106	0.2403	0.1884	0.1795	0.1902	0.2083
BTS_107	0.6943	0.5783	0.5783	0.5893	0.5245
BTS_108	0.4246	0.3048	0.2647	0.3875	0.3207
BTS_109	0.4938	0.3405	0.2494	0.4183	0.4125
BTS_110	0.3716	0.2979	0.2711	0.2853	0.3274
BTS_111	0.2736	0.1858	0.1841	0.2456	0.166
BTS_112	0.3313	0.2902	0.2902	0.2556	0.1818
BTS_113	0.4459	0.3752	0.3752	0.3718	0.3137
BTS_114	0.3456	0.2438	0.1895	0.3137	0.2326
BTS_115	0.3532	0.2713	0.2224	0.2146	0.3427
BTS_116	0.5577	0.3978	0.2599	0.4816	0.5039
BTS_117	0.4958	0.382	0.3328	0.3137	0.474
BTS_118	0.2581	0.194	0.1571	0.2138	0.2179
BTS_119	0.5154	0.332	0.2682	0.4689	0.348
BTS_120	0.5861	0.398	0.398	0.5776	0.4134
BTS_121	0.5671	0.4554	0.4554	0.5089	0.3426
BTS_122	0.3481	0.2668	0.233	0.2507	0.3115
BTS_123	0.267	0.2034	0.1832	0.2297	0.2203
BTS_124	0.3859	0.2897	0.206	0.3276	0.3211
BTS_125	0.375	0.2955	0.286	0.3229	0.3092
BTS_126	0.42	0.2942	0.2563	0.3897	0.2766
BTS_127	0.4082	0.3369	0.2915	0.255	0.3918
BTS_128	0.3799	0.2922	0.2133	0.2704	0.3491
BTS_129	0.388	0.346	0.346	0.2502	0.374
BTS_130	0.3481	0.2269	0.2081	0.3073	0.2237
BTS_131	0.157	0.09043	0.05538	0.1524	0.08991

BTS_132	1	0.8109	0.8109	0.9305	0.6587
BTS_133	0.6234	0.4312	0.3858	0.6072	0.4642
BTS_134	0.6428	0.4379	0.3654	0.6182	0.5056
BTS_135	0.8283	0.7739	0.7739	0.6163	0.7248
BTS_136	0.8659	0.7738	0.7738	0.8223	0.6975
BTS_137	0.3936	0.3194	0.3194	0.3392	0.3165
BTS_138	0.5427	0.4587	0.4587	0.3942	0.513
BTS_139	0.5517	0.4224	0.4224	0.4983	0.4139
BTS_140	0.4549	0.3895	0.3858	0.3972	0.36
BTS_141	0.5379	0.4307	0.3376	0.4478	0.418
BTS_142	0.5625	0.4315	0.3784	0.4768	0.5155
BTS_143	0.5838	0.4029	0.4029	0.5523	0.3886
BTS_144	0.3445	0.2657	0.1994	0.2019	0.3375
BTS_145	0.4698	0.4145	0.4055	0.3309	0.3558
BTS_146	0.4192	0.3262	0.2753	0.3357	0.3457
BTS_147	0.2246	0.1836	0.1715	0.1817	0.1924
BTS_148	0.4317	0.318	0.2846	0.3915	0.3047
BTS_149	0.2635	0.2036	0.1464	0.2319	0.1957
BTS_150	0.4918	0.3963	0.3963	0.4177	0.3934
BTS_151	0.4803	0.3135	0.1823	0.4441	0.3228
BTS_152	0.3097	0.2245	0.1749	0.2606	0.2591
BTS_153	0.3443	0.2795	0.25	0.2386	0.3183
BTS_154	0.4287	0.3179	0.3179	0.3882	0.2996
BTS_155	0.2915	0.2282	0.1799	0.2392	0.2476
BTS_156	0.4661	0.4255	0.4176	0.2857	0.4502
BTS_157	0.6698	0.6081	0.4736	0.5184	0.6133
BTS_158	0.3906	0.3046	0.2703	0.3284	0.327
BTS_159	0.6005	0.5003	0.4582	0.4458	0.5038
BTS_160	0.6469	0.5161	0.5161	0.5467	0.5398
BTS_161	0.3264	0.2545	0.2413	0.2645	0.2794
BTS_162	0.4476	0.359	0.3084	0.332	0.4015
BTS_163	0.6005	0.5575	0.5575	0.4063	0.5303
BTS_164	0.3158	0.2377	0.2131	0.2525	0.2557
BTS_165	0.2043	0.177	0.1521	0.1529	0.163
BTS_166	0.3201	0.2353	0.1778	0.2809	0.2565

BTS_167	0.2755	0.2691	0.2691	0.1755	0.1846
BTS_168	0.3812	0.3405	0.316	0.2308	0.3688
BTS_169	0.1865	0.1242	0.07379	0.1663	0.1369
BTS_170	0.5364	0.2727	0.2559	0.5025	0.3007
BTS_171	0.393	0.3468	0.3412	0.2556	0.3383
BTS_172	0.2957	0.2132	0.1901	0.2191	0.2551
BTS_173	0.9316	0.7383	0.7383	0.8103	0.6329
BTS_174	0.2004	0.1548	0.1169	0.1538	0.1769
BTS_175	0.3094	0.2479	0.1986	0.2506	0.2646
BTS_176	0.2439	0.1891	0.1422	0.1727	0.2237
BTS_177	0.6967	0.4402	0.4402	0.6504	0.4134
BTS_178	0.2142	0.1646	0.1215	0.1454	0.1997
BTS_179	0.4973	0.3958	0.2784	0.4138	0.4309
BTS_180	0.255	0.1749	0.1749	0.2364	0.1587
BTS_181	0.8357	0.5434	0.5434	0.7094	0.5119
BTS_182	0.6836	0.5535	0.4966	0.5064	0.613
BTS_183	0.8059	0.7579	0.6875	0.5182	0.6402
BTS_184	0.176	0.1509	0.1505	0.1123	0.1675
BTS_185	0.2426	0.206	0.206	0.202	0.1895
BTS_186	0.5527	0.4702	0.4312	0.3715	0.5167
BTS_187	0.5072	0.3282	0.2833	0.4865	0.3325
BTS_188	0.4722	0.3178	0.3063	0.4441	0.3192
BTS_189	0.4046	0.3136	0.2968	0.2998	0.2973
BTS_190	0.4327	0.3368	0.2938	0.3234	0.3858
BTS_191	0.9652	0.6442	0.6442	0.9029	0.5262
BTS_192	0.3196	0.2544	0.2193	0.2558	0.2753
BTS_193	0.4711	0.3261	0.2007	0.3908	0.4042
BTS_194	0.5188	0.3457	0.2334	0.4755	0.3391
BTS_195	0.329	0.2173	0.1876	0.2811	0.2198
BTS_196	0.4144	0.2928	0.204	0.3676	0.3162
BTS_197	0.4273	0.2763	0.2661	0.3768	0.2887
BTS_198	0.2466	0.1775	0.1517	0.1974	0.2125
BTS_199	0.3003	0.271	0.2238	0.1496	0.3003
BTS_200	0.5402	0.4118	0.3801	0.4789	0.4074
BTS_201	0.4082	0.2445	0.2425	0.3737	0.2142

BTS_202	0.4886	0.3952	0.3586	0.3551	0.3534
BTS_203	0.3493	0.2685	0.2297	0.2642	0.3043
BTS_204	0.5835	0.4659	0.4365	0.3949	0.5444
BTS_205	0.5722	0.4469	0.4469	0.4711	0.4848
BTS_206	0.4847	0.3679	0.2956	0.4244	0.3346
BTS_207	0.4141	0.3431	0.3242	0.3337	0.345
BTS_208	0.4869	0.4535	0.4535	0.322	0.3287
BTS_209	0.2888	0.2213	0.1729	0.2351	0.2536
BTS_210	0.5609	0.4601	0.3756	0.465	0.4868
BTS_211	0.3106	0.2426	0.233	0.2308	0.2778
BTS_212	0.7101	0.6206	0.5584	0.7101	0.5895
BTS_213	0.3179	0.2193	0.2181	0.2481	0.2517
BTS_214	0.4181	0.3851	0.3078	0.3206	0.4096
BTS_215	0.6016	0.5138	0.4607	0.495	0.4607
BTS_216	0.4017	0.3129	0.3129	0.3209	0.2857
BTS_217	0.4	0.3752	0.3752	0.2633	0.375
BTS_218	0.7798	0.6375	0.5803	0.3937	0.7798
BTS_219	0.3712	0.3159	0.2904	0.2477	0.3539
BTS_220	0.9232	0.9025	0.9025	0.4761	0.7595
BTS_221	0.5599	0.3957	0.3805	0.5122	0.4072
BTS_222	1	1	1	0.8954	1
BTS_223	0.5506	0.2962	0.2471	0.5506	0.2595
BTS_224	0.6139	0.5328	0.5258	0.4648	0.5422
BTS_225	0.3587	0.3524	0.3524	0.2611	0.3202
BTS_226	0.456	0.3356	0.2678	0.3509	0.3884
BTS_227	0.7313	0.5195	0.4718	0.5673	0.5802
BTS_228	0.6364	0.6364	0.5978	0.4734	0.6155
BTS_229	1	0.927	0.927	1	0.856
BTS_230	0.8282	0.8135	0.8135	0.7627	0.7039
BTS_231	0.6181	0.61	0.5056	0.5164	0.6181
BTS_232	0.8383	0.7531	0.7531	0.6874	0.6571
BTS_233	0.5687	0.56	0.5213	0.4785	0.5687
BTS_234	0.575	0.575	0.575	0.2245	0.4151
BTS_235	0.416	0.3766	0.3766	0.3325	0.3602
BTS_236	0.4872	0.4069	0.3208	0.2848	0.4777

BTS_237	0.839	0.7225	0.7225	0.7915	0.708
BTS_238	0.3372	0.2782	0.2782	0.25	0.3011
BTS_239	0.4066	0.2838	0.2272	0.3699	0.2741
BTS_240	0.6155	0.5911	0.5629	0.5722	0.5866
BTS_241	0.3283	0.2469	0.2127	0.2934	0.2514
BTS_242	0.2747	0.2073	0.189	0.2347	0.2249
BTS_243	0.346	0.2877	0.2689	0.2619	0.3124
BTS_244	0.4477	0.2758	0.2699	0.4085	0.2635
BTS_245	0.3221	0.2903	0.2709	0.2102	0.2716
BTS_246	0.593	0.4473	0.3536	0.4655	0.5167
BTS_247	0.2696	0.2021	0.143	0.2108	0.2355
BTS_248	0.4035	0.2918	0.2607	0.3635	0.3021
BTS_249	0.2648	0.2196	0.1928	0.2044	0.2319
BTS_250	0.3726	0.1575	0.1194	0.3726	0.1625
BTS_251	0.4618	0.2993	0.2869	0.3971	0.2896
BTS_252	0.4576	0.3818	0.3482	0.2475	0.4576
BTS_253	0.3386	0.2465	0.2392	0.3087	0.2427
BTS_254	0.5387	0.4628	0.4253	0.4091	0.4738
BTS_255	0.7061	0.5592	0.5592	0.5909	0.4511
BTS_256	0.8171	0.7222	0.7222	0.5245	0.8171
BTS_257	0.4382	0.3134	0.2421	0.3557	0.3744
BTS_258	0.3784	0.2427	0.2212	0.3656	0.2436
BTS_259	0.8599	0.6755	0.57	0.6068	0.7899
BTS_260	0.6871	0.6871	0.6871	0.4634	0.6281
BTS_261	0.381	0.3795	0.3795	0.2341	0.2507
BTS_262	0.4752	0.339	0.3287	0.4228	0.3891
BTS_263	0.2561	0.199	0.1884	0.1924	0.1818
BTS_264	0.8905	0.8299	0.8299	0.6669	0.7662
BTS_265	0.5874	0.4359	0.376	0.4944	0.4914
BTS_266	0.5805	0.5016	0.5016	0.4588	0.4425
BTS_267	0.2465	0.1974	0.1542	0.1785	0.2238
BTS_268	0.2171	0.1753	0.1239	0.1385	0.2069
BTS_269	0.347	0.3079	0.2876	0.257	0.3151
BTS_270	0.2475	0.2034	0.1642	0.1204	0.2475
BTS_271	0.2694	0.181	0.1293	0.243	0.2027

BTS_272	0.42	0.3358	0.2902	0.2959	0.3859
BTS_273	0.4267	0.292	0.2537	0.3582	0.3534
BTS_274	0.2515	0.1807	0.16	0.2211	0.2008
BTS_275	0.3654	0.2986	0.2629	0.2703	0.3342
BTS_276	1	0.9513	0.9513	0.9364	0.8734
BTS_277	0.3723	0.2912	0.279	0.2909	0.3249
BTS_278	0.4445	0.3523	0.3225	0.3398	0.3798
BTS_279	0.8026	0.7903	0.7903	0.5151	0.6167
BTS_280	0.5172	0.4085	0.3995	0.3757	0.426
BTS_281	0.96	0.96	0.96	0.3166	0.8151
BTS_282	1	1	0.9105	0.8863	0.7294
BTS_283	0.6335	0.5873	0.5873	0.3691	0.6335
BTS_284	1	1	1	1	0.827
BTS_285	1	1	1	0.7647	1
BTS_286	1	1	1	0.6892	1
BTS_287	0.674	0.6542	0.6542	0.4443	0.674
BTS_288	0.5798	0.5798	0.5798	0.2489	0.4317
BTS_289	0.7222	0.7222	0.7222	0.3631	0.5268
BTS_290	1	1	1	1	1
BTS_291	0.3265	0.2827	0.2827	0.257	0.2826
BTS_292	0.343	0.2653	0.2528	0.3051	0.2308
BTS_293	0.398	0.2893	0.2893	0.364	0.2864
BTS_294	0.4229	0.3235	0.3055	0.3432	0.3616
BTS_295	0.3913	0.3165	0.3005	0.3034	0.282
BTS_296	0.3698	0.3112	0.2614	0.309	0.3057
BTS_297	0.6397	0.4145	0.4145	0.6104	0.3901
BTS_298	0.5393	0.4	0.4	0.5017	0.3475
BTS_299	0.3074	0.2321	0.1943	0.2606	0.1972
BTS_300	0.6047	0.4555	0.3731	0.4664	0.5321
BTS_301	0.6422	0.4877	0.405	0.5125	0.5545
BTS_302	0.7713	0.577	0.577	0.7314	0.4887
BTS_303	0.4725	0.3549	0.2707	0.3991	0.3945
BTS_304	1	0.7908	0.6917	0.7233	0.9095
BTS_305	0.332	0.2558	0.2558	0.2951	0.2587
BTS_306	0.4992	0.3485	0.2604	0.4591	0.2934

BTS_307	0.6592	0.5596	0.5343	0.4499	0.6115
BTS_308	0.8198	0.67	0.6398	0.572	0.7149
BTS_309	0.5639	0.4179	0.381	0.4513	0.4861
BTS_310	0.544	0.3548	0.2539	0.4942	0.3848
BTS_311	0.4879	0.3151	0.284	0.4469	0.3537
BTS_312	0.3856	0.32	0.3001	0.2948	0.3396
BTS_313	1	0.8224	0.8224	0.8679	0.8204
BTS_314	0.3722	0.2914	0.2545	0.2631	0.3416
BTS_315	0.5876	0.5678	0.5429	0.3493	0.5479
BTS_316	0.5987	0.4663	0.4482	0.4327	0.5138
BTS_317	0.6919	0.6919	0.6919	0.2675	0.5931
BTS_318	0.9145	0.9145	0.9145	0.3807	0.8152
BTS_319	0.5843	0.5685	0.5685	0.4374	0.3539
BTS_320	0.7515	0.7216	0.7216	0.5423	0.4701
BTS_321	0.3761	0.3761	0.3761	0.2169	0.2722
BTS_322	0.4065	0.4031	0.4031	0.2551	0.3855
BTS_323	0.2067	0.2012	0.1969	0.121	0.1921
BTS_324	0.5665	0.4941	0.3213	0.1835	0.5665
BTS_325	0.9873	0.9359	0.9359	0.2452	0.9873
BTS_326	1	0.7786	0.7616	1	0.7156
BTS_327	0.854	0.854	0.854	0.4659	0.5924
BTS_328	0.4045	0.3858	0.3858	0.2917	0.2728
BTS_329	0.8804	0.7277	0.7277	0.8128	0.4106
BTS_330	0.7069	0.5837	0.5837	0.6093	0.4946
BTS_331	0.7764	0.6906	0.6906	0.5798	0.6384
BTS_332	0.5625	0.4818	0.3822	0.4327	0.5012
BTS_333	0.779	0.5354	0.5212	0.6299	0.4988
BTS_334	0.4112	0.3395	0.3018	0.3126	0.3634
BTS_335	0.903	0.6334	0.6334	0.7636	0.6135
BTS_336	0.8726	0.6984	0.6984	0.7236	0.5597
BTS_337	0.9075	0.5621	0.5144	0.8151	0.601
BTS_338	0.8838	0.6682	0.6682	0.7989	0.6619
BTS_339	0.3641	0.3016	0.267	0.2439	0.3411
BTS_340	0.2386	0.1779	0.17	0.183	0.2105
BTS_341	0.3989	0.3113	0.2794	0.3309	0.3366

BTS_342	0.4326	0.4082	0.3183	0.3053	0.4175
BTS_343	0.3736	0.3316	0.3316	0.2597	0.3428
BTS_344	0.6799	0.5248	0.5248	0.6196	0.4992
BTS_345	0.2952	0.2545	0.2537	0.2041	0.2719
BTS_346	0.726	0.5818	0.5459	0.5244	0.5338
BTS_347	0.8767	0.5283	0.514	0.765	0.5822
BTS_348	0.8478	0.766	0.766	0.6542	0.7148
BTS_349	0.9982	0.8661	0.8661	0.7353	0.605
BTS_350	0.8031	0.7251	0.7251	0.5927	0.6748
BTS_351	0.5155	0.3182	0.3182	0.4735	0.248
BTS_352	0.9862	0.613	0.5774	0.8679	0.5187
BTS_353	1	0.9738	0.9738	0.7547	0.8711
BTS_354	0.8921	0.7111	0.5998	0.6485	0.8087
BTS_355	0.9313	0.9313	0.9313	0.3884	0.6363
BTS_356	0.5149	0.5149	0.5149	0.1905	0.4433
BTS_357	0.8734	0.8593	0.8593	0.6331	0.666
BTS_358	0.8694	0.8694	0.8694	0.3896	0.8301
BTS_359	0.5775	0.4601	0.4367	0.4143	0.4488
BTS_360	0.4386	0.3592	0.3455	0.3229	0.3419
BTS_361	0.3036	0.2172	0.2172	0.2887	0.1826
BTS_362	0.7137	0.5071	0.4904	0.6363	0.5068
BTS_363	0.2781	0.2015	0.1836	0.2447	0.2117
BTS_364	0.7582	0.5596	0.494	0.689	0.5687
BTS_365	0.3132	0.2663	0.2479	0.1888	0.3041
BTS_366	0.2782	0.2201	0.1799	0.2214	0.2406
BTS_367	0.6458	0.4667	0.4535	0.5756	0.4998
BTS_368	0.2868	0.2117	0.1915	0.2494	0.2319
BTS_369	0.2692	0.2039	0.2031	0.2289	0.2238
BTS_370	0.4129	0.3251	0.2964	0.3561	0.3418
BTS_371	0.2176	0.1877	0.1496	0.1407	0.2064
BTS_372	0.3151	0.2754	0.2465	0.2171	0.2966
BTS_373	0.7926	0.6666	0.6666	0.6613	0.639
BTS_374	0.5647	0.4663	0.4663	0.3971	0.4651
BTS_375	0.5123	0.3848	0.3329	0.416	0.4379
BTS_376	0.3476	0.2548	0.2462	0.2931	0.2439

BTS_377	0.3109	0.2564	0.2437	0.2525	0.2486
BTS_378	0.3851	0.3155	0.2819	0.2906	0.3417
BTS_379	0.2934	0.2391	0.233	0.2239	0.2587
BTS_380	0.2201	0.2201	0.2201	0.1126	0.2047
BTS_381	0.437	0.3209	0.2388	0.3162	0.3974
BTS_382	0.4536	0.3992	0.3703	0.3115	0.4063
BTS_383	0.6918	0.5446	0.5171	0.5451	0.4685
BTS_384	0.3757	0.3085	0.2603	0.282	0.3254
BTS_385	0.3089	0.2469	0.2063	0.1947	0.2957
BTS_386	0.3281	0.2615	0.2205	0.2486	0.2912
BTS_387	0.9079	0.5804	0.5804	0.8975	0.4133
BTS_388	1	0.9155	0.8412	0.8034	0.8349
BTS_389	0.2697	0.2218	0.2218	0.2241	0.2269
BTS_390	0.6137	0.4797	0.4448	0.5131	0.5155
BTS_391	0.3388	0.2715	0.2715	0.2948	0.2764
BTS_392	0.5452	0.4688	0.4688	0.4363	0.4231
BTS_393	0.4599	0.3591	0.3315	0.3364	0.4227
BTS_394	0.495	0.4108	0.4023	0.3395	0.4183
BTS_395	0.6161	0.3006	0.2511	0.6037	0.2744
BTS_396	0.2904	0.1836	0.1521	0.2842	0.1744
BTS_397	0.3596	0.2859	0.24	0.2686	0.3217
BTS_398	0.2701	0.2172	0.2031	0.2141	0.2338
BTS_399	0.3789	0.2474	0.1787	0.3384	0.2803
BTS_400	0.3811	0.3042	0.2292	0.2403	0.3648
BTS_401	0.3392	0.2823	0.2823	0.2867	0.2826
BTS_402	0.6707	0.502	0.3814	0.485	0.6101
BTS_403	0.2605	0.1882	0.146	0.2308	0.1817
BTS_404	0.5519	0.4686	0.4469	0.3382	0.5332
BTS_405	0.5156	0.5017	0.4682	0.3273	0.462
BTS_406	0.3763	0.3197	0.262	0.2417	0.3579
BTS_407	0.4203	0.3551	0.3034	0.3284	0.3634
BTS_408	0.586	0.4286	0.3452	0.522	0.4338
BTS_409	0.4599	0.3682	0.3464	0.3746	0.3191
BTS_410	0.4625	0.4058	0.4058	0.3345	0.417
BTS_411	0.447	0.3493	0.2993	0.356	0.3864

BTS_412	0.5926	0.4262	0.3434	0.52	0.3973
BTS_413	0.3664	0.291	0.2545	0.3142	0.2932
BTS_414	0.4232	0.3132	0.2616	0.3788	0.3245
BTS_415	0.4888	0.4337	0.4203	0.319	0.3998
BTS_416	0.2232	0.1751	0.1463	0.1777	0.193
BTS_417	0.3233	0.275	0.2262	0.2659	0.2812
BTS_418	0.3346	0.23	0.2151	0.3092	0.2199
BTS_419	0.396	0.325	0.325	0.3385	0.2601
BTS_420	0.5418	0.5038	0.5038	0.3618	0.4936
BTS_421	0.5701	0.408	0.3847	0.5172	0.4231
BTS_422	0.3176	0.2732	0.2732	0.2219	0.1795
BTS_423	0.6326	0.5747	0.5747	0.4815	0.531
BTS_424	0.3644	0.3644	0.3644	0.1883	0.3439
BTS_425	0.464	0.3877	0.3413	0.3319	0.4414
BTS_426	0.5166	0.366	0.3022	0.4416	0.4279
BTS_427	0.1872	0.1351	0.1228	0.1718	0.1346
BTS_428	0.5793	0.5513	0.5341	0.3906	0.3579
BTS_429	0.729	0.6384	0.6172	0.5086	0.6704
BTS_430	0.3716	0.2507	0.2194	0.3012	0.2543
BTS_431	0.4796	0.3491	0.2885	0.4118	0.3886
BTS_432	0.6231	0.4772	0.4679	0.4711	0.432
BTS_433	1	1	1	0.5651	0.9338
BTS_434	0.6793	0.6644	0.6035	0.4857	0.6793

Appendix C: Category 2 (High Opportunity BTSs) with the Reference Set

Accessibility Model

BTS	BTS Efficiency AM	BTS_222	BTS_285	BTS_286
BTS_101	0.4809	0.0425	0	0.9574
BTS_105	0.2834	0	0.1538	0.8461
BTS_138	0.4587	0.0212	0	0.9787
BTS_19	0.4798	0	0.1538	0.8461
BTS_191	0.6442	0.0425	0	0.9574
BTS_227	0.5195	0.0170	0.0920	0.8908
BTS_259	0.6755	0	0.1538	0.8461
BTS_302	0.577	0.0425	0	0.9574
BTS_373	0.6666	0.0425	0	0.9574
BTS_47	0.6278	0	0.1538	0.8461
BTS_71	0.4317	0	0.1538	0.8461
BTS_75	0.4331	0	0.1538	0.8461
BTS_76	0.3807	0	0.1538	0.8461
BTS_77	0.5122	0	0.1538	0.8461

Retainability Model

BTS	BTS Efficiency RM	BTS_36	BTS_222	BTS_286
BTS_101	0.4809	0	0.0425	0.9574
BTS_105	0.2578	0	0.0425	0.9574
BTS_138	0.4587	0	0.0212	0.9574
BTS_19	0.4075	0	0.0425	0.9574
BTS_191	0.6442	0	0.0425	0.9574
BTS_227	0.4718	0.4482	0.0139	0.9574
BTS_259	0.57	0	0.0425	0.9574
BTS_302	0.577	0	0.0425	0.9574
BTS_304	0.6917	0.4435	0.0142	0.9574
BTS_373	0.6666	0	0.0425	0.9574
BTS_47	0.5692	0	0.0425	0.9574
BTS_71	0.371	0	0.0425	0.9574
BTS_75	0.4249	0	0.0425	0.9574
BTS_76	0.3063	0	0.0425	0.9574
BTS_77	0.4448	0	0.0425	0.9574

Mobility Model

BTS	BTS Efficiency MM	BTS_38	BTS_326
BTS_105	0.2514	1	0
BTS_138	0.3942	0.6666	0.3333
BTS_19	0.5145	1	0
BTS_227	0.5673	1	0
BTS_259	0.6068	1	0
BTS_373	0.6613	1	0
BTS_47	0.485	1	0
BTS_71	0.5578	1	0
BTS_75	0.4241	1	0
BTS_76	0.4277	1	0
BTS_77	0.4983	1	0

Service Integrity Model

BTS	BTS Efficiency SIM	BTS_222	BTS_286
BTS_101	0.4428	0.0425	0.9574
BTS_105	0.3077	0.0425	0.9574
BTS_132	0.6587	0.0212	0.9787
BTS_138	0.513	0.0212	0.9787
BTS_19	0.5359	0.0425	0.9574
BTS_191	0.5262	0.0425	0.9574
BTS_227	0.5802	0.0425	0.9574
BTS_302	0.4887	0.0425	0.9574
BTS_373	0.639	0.0425	0.9574
BTS_38	0.5583	0.0425	0.9574
BTS_71	0.488	0.0425	0.9574
BTS_75	0.4848	0.0425	0.9574
BTS_76	0.4483	0.0425	0.9574
BTS_77	0.5363	0.0425	0.9574

Appendix D: Letter of Invitation to Experts

This letter was attached to the email that was sent to the experts to participate and join the consultation.

Portland State UNIVERSITY

Invitation Letter/Email

Re: Invitation to be an expert in Maoloud Dabab's PhD research

Dear Mr. / Ms.:

My name is Maoloud Dabab, and I am a Ph.D. student in Engineering and Technology Management Department (ETM) at Portland State University (PSU). I am conducting my dissertation research entitled "An Assessment of the DMUs' Efficiency in Service Systems: The Case of Libyan Cellular Telecom".

As part of my research, I am forming experts to help me validate my research model and the results. I have identified you as an expert in this field. Your knowledge, background, experience, and expertise will be very helpful for my research.

If you agree to participate in this research, a consent form will be sent to you for signature. After I receive the signed form, I will send you web-based data collection instruments for you to provide your response. The research instruments will take about 10 ~15 minutes each to complete.

I will be honored if you could accept my invitation and join the expert panel. I would also appreciate greatly if you could suggest other experts who have expertise or experiences in mobile radio optimization and planning filed.

As a token of appreciation, I will be glad to send you an electronic copy of the research upon completion.

I look forward to receiving your reply

Sincerely,

Maoloud Dabab
PhD Student
Portland State University
Engineering and Technology Management Department
Phone: +1971-533-1459
Email: dabab@pdx.edu

Appendix E: Qualtrics Surveys to Evaluate the Model

Maoloud Dabab's Research Model Validation

ETM
ENGINEERING & TECHNOLOGY MANAGEMENT

Portland State

An Assessment of Mobile Base Station Efficiency Survey

The objective of my research is to develop a decision model to enable better decision making within the Mobile Base Station operation by identifying best practices from efficient Base Stations and forming the reference set for inefficient Base Stations.

This will help decision-makers determine where they can invest in improvements by evaluating the performance of Base Stations and improving the configuration of the inefficient Base Stations.

The research focuses on 2G mobile technology.

Survey Objective:
The objective of this survey is to validate the exploratory list of Key Performance Indicators that were identified based on a comprehensive literature review and my personal experience. These KPIs will be used as inputs and outputs to assess the efficiency of the BTS. The following questions are intended to capture your perspective of the suitability of those KPIs and to identify those that might have been missed during my literature review. Your input will be used to help finalize my model.

Experts Validation Process:
In the following pages, you will be asked to judge the most critical KPIs for evaluating the efficiency of the BTS. You can also suggest other KPIs based on your experience, and you will be able to add your comments and concerns in each page.

Note: These abbreviations will be used in the survey

- Key Performance Indicator (KPI)
- Base Transceiver Station (BTS)

Please click on the next button (-->) on the right bottom of the screen

Questions

Maoloud Dabab's Research Model Validation

Please enter your name:

First Name

Last Name

Maoloud Dabab's Research Model Validation (Page 1/6)

KPIs for a comprehensive BTS efficiency model:

Input		Output	
KPI 1	Time slot (TCH)	KPI 3	Traffic (Erlang)
		KPI 4	SDCCH Traffic (Erlang)
		KPI 5	Random Access Success
		KPI 6	TCH Success
		KPI 7	SDCCH Success
KPI 2	Time slot (SDCCH)	KPI 8	Handover Success
		KPI 9	Speech Good Quality

Input

KPI 1: Number of TCH time slots: the number of time slots in the physical units, TRU, that specify the capacity of the cell. Depending on the configuration, each TRU can serve between eight and sixteen users simultaneously.

KPI 1: Number of SDCCH time slots: the number of time slots in the physical units, TRU, that specify the capacity of the signaling. Depending on the configuration, each TRU can serve between sixty-four and one hundred twenty-eight users simultaneously.

Output:

KPI 3: TCH Traffic (Erlang): used to measure the traffic density for the TCH channel during a time window where one Erlang is equal to one hour of traffic. A TCH channel is used to carry voice or data traffic.

KPI 4: SDCCH Traffic (Erlang): used to measure the traffic density for the SDCCH channel during a time window where one Erlang is equal to one hour of traffic. SDCCH traffic is used to carry short message traffic or for network signaling.

KPI 5: Random Access Success: the number of successful attempts by all of the subscribers on the cell when randomly attempting to get an SDCCH channel.

KPI 6: TCH Success: the number of successful TCH assignment to all subscribers on the cell.

KPI 7: SDCCH Success: the number of successful SDCCH assignment to all subscribers on the cell.

KPI 8: Handover Success: the number of successful times when the subscriber "who has TCH or SDCCH resource" moved from one cell to another cell.

KPI 9: Speech Good Quality: the quality of the speech during the call experienced by the end user.

Are these KPIs above appropriate to measure the **overall efficiency** of the BTS?

	Yes	No
TCH time slots (KPI 1)		
SDCCH time slots (KPI 2)		
TCH Traffic (KPI 3)		
SDCCH Traffic (KPI 4)		
Random Access Success (KPI 5)		
TCH Success (KPI 6)		
SDCCH Succeed (KPI 7)		
Handover Success (KPI 9)		
Speech Good Quality (KPI 9)		

If you think that there are other KPIs or you have comments and concerns about the listed KPIs, please provide it here.

Maoloud Dabab's Research Model Validation (Page 2/5)

KPIs for the accessibility of the BTS:

Input		Output	
KPI 1	Time slot (TCH)	KPI 3	Traffic (Erlang)
		KPI 4	SDCCH Traffic (Erlang)
		KPI 5	Random Access Success
		KPI 6	TCH Success
KPI 2	Time slot (SDCCH)	KPI 7	SDCCH Success
		KPI 8	Handover Success
		KPI 9	Speech Good Quality

Input

KPI 1: Number of TCH time slots: the number of time slots in the physical units, TRU, that specify the capacity of the cell. Depending on the configuration, each TRU can serve between eight and sixteen users simultaneously.

KPI 2: Number of SDCCH time slots: the number of time slots in the physical units, TRU, that specify the capacity of the signaling. Depending on the configuration, each TRU can serve between sixty-four and one hundred twenty-eight users simultaneously.

Outputs

KPI 3: TCH Traffic (Erlang): used to measure the traffic density for the TCH channel during a time window where one Erlang is equal to one hour of traffic. A TCH channel is used to carry voice or data traffic.

KPI 4: SDCCH Traffic (Erlang): used to measure the traffic density for the SDCCH channel during a time window where one Erlang is equal to one hour of traffic. SDCCH traffic is used to carry short message traffic or the network signaling.

KPI 5: Random Access Success: the number of successful attempts by all of the subscribers on the cell when randomly attempting to get an SDCCH channel.

KPI 6: TCH Success: the number of successful TCH assignment to all subscribers on the cell.

KPI 7: SDCCH Success: the number of successful SDCCH assignment to all subscribers on the cell.

Are these KPIs appropriate to measure of the **accessibility** of the BTS and how efficient the customers can reach the BTS?

	Yes	No
TCH time slots (KPI 1)	◯	◯
SDCCH time slots (KPI 2)	◯	◯
TCH Traffic (KPI 3)	◯	◯
SDCCH Traffic (KPI 4)	◯	◯
Random Access Success (KPI 5)	◯	◯
TCH Success (KPI 6)	◯	◯
SDCCH Success (KPI 7)	◯	◯

If you think that there are other KPIs or you have comments and concerns about the listed KPIs, please provide it here.

Maoloud Dabab's Research Model Validation page (3/5)

KPIs for the BTS's retainability:

Input		Output	
KPI 1	Time slot (TCH)	KPI 3	Traffic (Erlang)
		KPI 4	SDCCH Traffic (Erlang)
		KPI 5	Random Access Success
		KPI 6	TCH Success
KPI 2	Time slot (SDCCH)	KPI 7	SDCCH Success
		KPI 8	Handover Success
		KPI 9	Speech Good Quality

Input

KPI 1: Number of TCH time slots: the number of time slots in the physical units, TRU, that specify the capacity of the cell. Depending on the configuration, each TRU can serve between eight and sixteen users simultaneously.

KPI 2: Number of SDCCH time slots: the number of time slots in the physical units, TRU, that specify the capacity of the signaling. Depending on the configuration, each TRU can serve between sixty-four and one hundred twenty-eight users simultaneously.

Outputs

KPI 6: TCH Success: the number of successful TCH assignment to all subscribers on the cell.

KPI 7: SDCCH Success: the number of successful SDCCH assignment to all subscribers on the cell.

Are these KPIs appropriate to measure of the BTS's **retainability** and the ability to continue providing the service?

	Yes	No
TCH time slots (KPI 1)	◯	◯
SDCCH time slots (KPI 2)	◯	◯
TCH Success (KPI 6)	◯	◯
SDCCH Success (KPI 7)	◯	◯

If you think that there are other KPIs or you have comments and concerns about the listed KPIs, please provide it here.

Maoloud Dabab's Research Model Validation page (4/5)

KPIs for the mobility of BTS:

Input		Output	
KPI 1	Time slot (TCH)	KPI 3	Traffic (Erlang)
		KPI 4	SDCCH Traffic (Erlang)
		KPI 5	Random Access Success
		KPI 6	TCH Success
KPI 2	Time slot (SDCCH)	KPI 7	SDCCH Success
		KPI 8	Handover Success
		KPI 9	Speech Good Quality

Input

KPI 1: Number of TCH time slots: the number of time slots in the physical units, TRU, that specify the capacity of the cell. Depending on the configuration, each TRU can serve between eight and sixteen users simultaneously.

KPI 2: Number of SDCCH time slots: the number of time slots in the physical units, TRU, that specify the capacity of the signaling. Depending on the configuration, each TRU can serve between sixty-four and one hundred twenty-eight users simultaneously.

Outputs

KPI 8: Handover Success: the number of successful times when the subscriber "who has TCH or SDCCH resource" moved from one cell to another cell.

Are these KPIs above appropriate to measure of the **mobility** and the fluency of handover calls while customers are moving from and to the BTS?

	Yes	No
TCH time slots (KPI 1)		
SDCCH time slots (KPI 2)		
Handover Success (KPI 8)		

If you think that there are other KPIs or you have comments and concerns on the listed KPIs, please provide it here.

Maoloud Dabab's Research Model Validation page (5/5)

KPIs for BTS's service integrity:

Input		Output	
KPI 1	Time slot (TCH)	KPI 3	Traffic (Erlang)
		KPI 4	SDCCH Traffic (Erlang)
		KPI 5	Random Access Success
		KPI 6	TCH Success
KPI 2	Time slot (SDCCH)	KPI 7	SDCCH Success
		KPI 8	Handover Success
		KPI 9	Speech Good Quality

Input

KPI 1: Number of TCH time slots: the number of time slots in the physical units, TRU, that specify the capacity of the cell. Depending on the configuration, each TRU can serve between eight and sixteen users simultaneously.

KPI 2: Number of SDCCH time slots: the number of time slots in the physical units, TRU, that specify the capacity of the signaling. Depending on the configuration, each TRU can serve between sixty-four and one hundred twenty-eight users simultaneously.

Outputs

KPI 9: Speech Good Quality: the quality of the speech during the call experienced by the end user.

Are these KPIs appropriate to measure the **service integrity**, which represents the quality of speech during the calls?

	Yes	No
TCH time slots (KPI 1)		
SDCCH time slots (KPI 2)		
Speech Good Quality (KPI 9)		

If you think that there are other KPIs or you have comments and concerns about the listed KPIs, please provide it here.

If you have any comments and concerns on overall research and the models, please provide it here.

Submission Confirmation

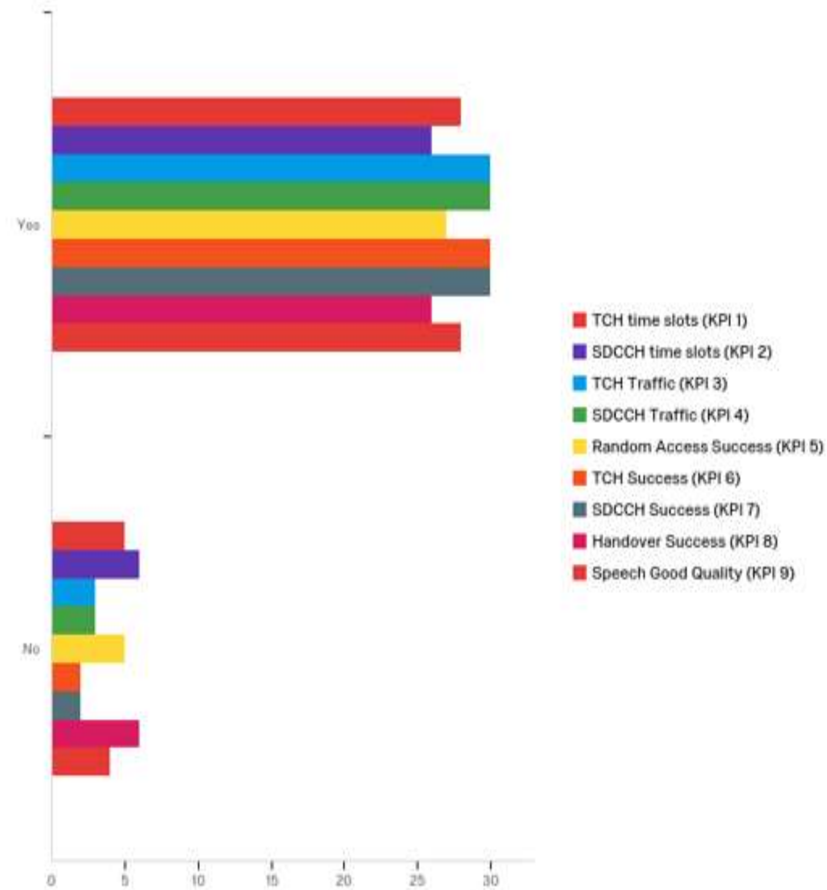
By clicking on the " -->" button, your answers will be submitted.

Thank you.

Appendix F: The Results of the Qualtrics Surveys

The Research Model Validation Survey

Q1-1 - Are these KPIs above appropriate to measure the overall efficiency **of the BTS?**



Q1-2 - If you think that there are other KPIs or you have comments and concerns about the listed KPIs, please provide it here.

generally, in most cases the faults/Alarms in the sites has major impact on Overall BTS efficiency, but in few cases when there is alarms appeared the mentioned KPI's doesn't reflect the real performance (i.e. no impact on KPI's but there is impact on user).

Subscriber Perceived TCH Congestion (%)

Most KPIs for voice service are covered

Call setup success ratio, and drop call rates can be added. The speech quality needs more definition whether it will be based on POLQA or other methods. Interference rates can also be added as a KPI

The TCH /SDCCH time slots that's the configuration of BTS it means how many TCH /SDCCH/PDCH for each TRX inside the CELL usually we use 4 TRX each cell (each TRX have eaith Time slots usually first time slot we configure it for SDCCH and one or two for PDCH and others for TCH) inside the BTS as default then if there congestion we make expansion TCH is for voice traffic SDCCH is for signaling PDCH for Data traffic All above is configuration of BTS not evaluation of BTS ...... Below is main GSM KPI's that used to evaluate the performance of any GSM network 1-Traffic volume on TCH/SDCCH 2-TCH/SDCCH congestion rate % 3-SDCCH Drop rate % 4-TCH Call Drop rate % (including /excluding Handover 5-immediate Assignment success rate% 6-Assignment success rate % 7-Handover success rate % 8-Call setup success rate % 9-Inter BSC outgoing Handover success rate % 10- TCH availability 11-Downlink /Uplink TBF Establishment success rate 12-Downlink /Uplink TBF Drop rate 13-Downlink /Uplink EGPRS TBF Drop rate 14-Average throughput of Downlink EGPRS/GPRS RLC per PDCH (Kbit/s) 15-DL/UL _HQI (%) .... Will send you clarification on above KPI's ....

Cell Utilization. for Random Access Success I think it has non-direct relation with efficiency since for example if it was degraded , it prevents calls occur.

maybe you can add drop call rate

the listed KPIs is 2G KPIs , the BTS (as HW) it serve more than one technology so what about other technology ?

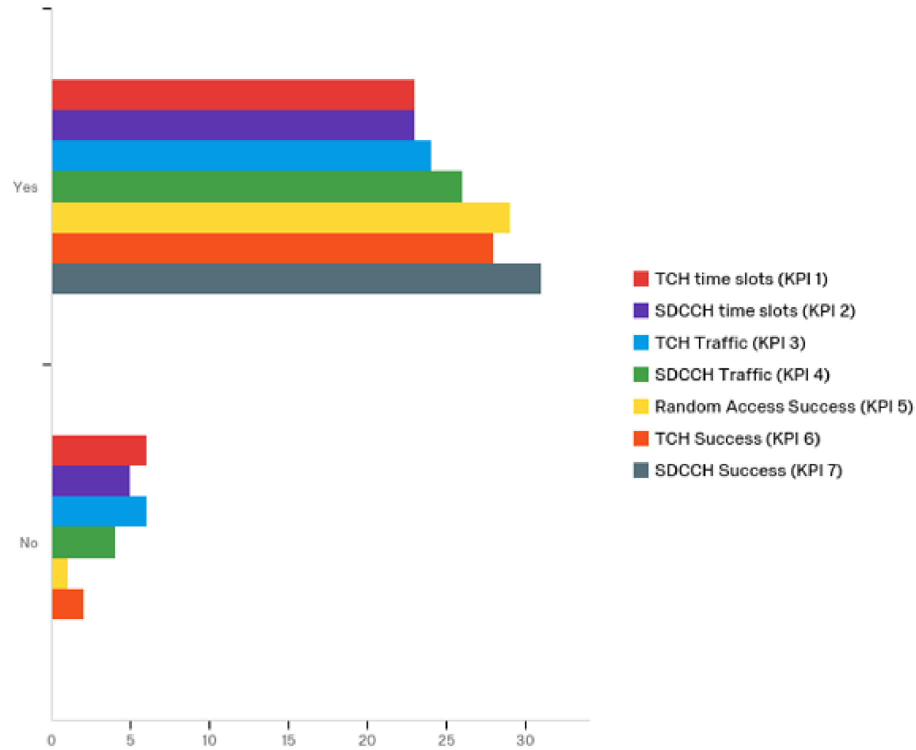
The number of TCHs and Sdcchs Channels does not really reflect the performance of the BTS as they ate fixed values depends on the number of TRXs per cell and the setting provided by the Radio Engineer. They are not KPIs.

Additionally, you might want to look at: -Call drop rate. -Call setup success rate.

it's better to insert ICMBand as a third input

KPI2: If I am not wrong, there is a bottleneck here, because SDCCH is limited by the amount of TCH. If there is no TCH available to connect the call, the SDCCH limitation is not important. KPI4: In this case, since this is the average per hour, you could use it to compare the average amount of call attempts (SDCCH Erlangs) and the average amount of calls that were really connected (TCH Erlangs). Therefore, this is more useful than KPI2. KPI5: I am not sure, is it the same as I have explained in previous KPI4 description? KPI8: In this case, what will you measure? In case that handover is successful or it fails, which BTS is the responsible, the original or the destination BTS while handover is done? I am not sure in the BTS, but I know in the MSC you can obtain some KPIs about the calls unexpectedly dropped. As a subscriber and as a provider, I would say that it is a very important KPI.

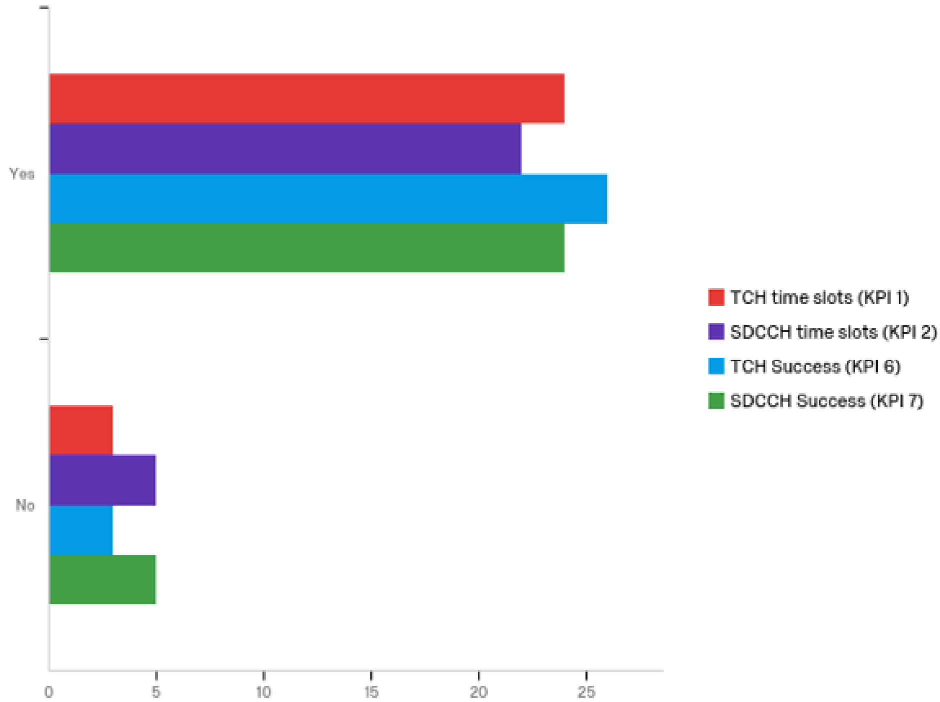
Q2-1 - Are these KPIs appropriate to measure of the accessibility of the BTS and how efficient the customers can reach the BTS?



Q2-2 - If you think that there are other KPIs or you have comments and concerns about the listed KPIs, please provide it here.

Subscriber Perceived TCH Congestion (%)
Regarding the accessibility the SDCCH drop rate and Call setup TCH congestion rate, these two are important KPIs indicate the following problems and may cause inefficient access to the BTS: 1) Low signal strength on down or uplink 2) Poor quality on down or uplink 3) Too high timing advance. 4) Congestion on TCH. 5) Increasing traffic demand. 6) Bad dimensioning. 7) High mean holding Time (MHT). 8) Low handover activity. 9) Congestion in surrounding cell.
Quality will be affected if you're on half rate, also accessibility will be affected depending on what band you are using GSM900 or DCS, I'm assuming you are using GSM as 2G (not CDMA IS95)
none
For accessibility you might find it useful to include TCH and SDCCH congestion rates. It is also arguable that Handover success rate is relevant.
- Dear, for sure you are going to calculate TCH congestion here as well. - How would you treat PDCH channels during your medel calcultaion to measure the accessibility?
the Service accessibility is "The ability of a service to be obtained, requested by the user."! so the mentioned KPIs are good to measure the accessibility.
In this case, if my English is not wrong, KPI3 and 4, are more about the quality than the accessibility?

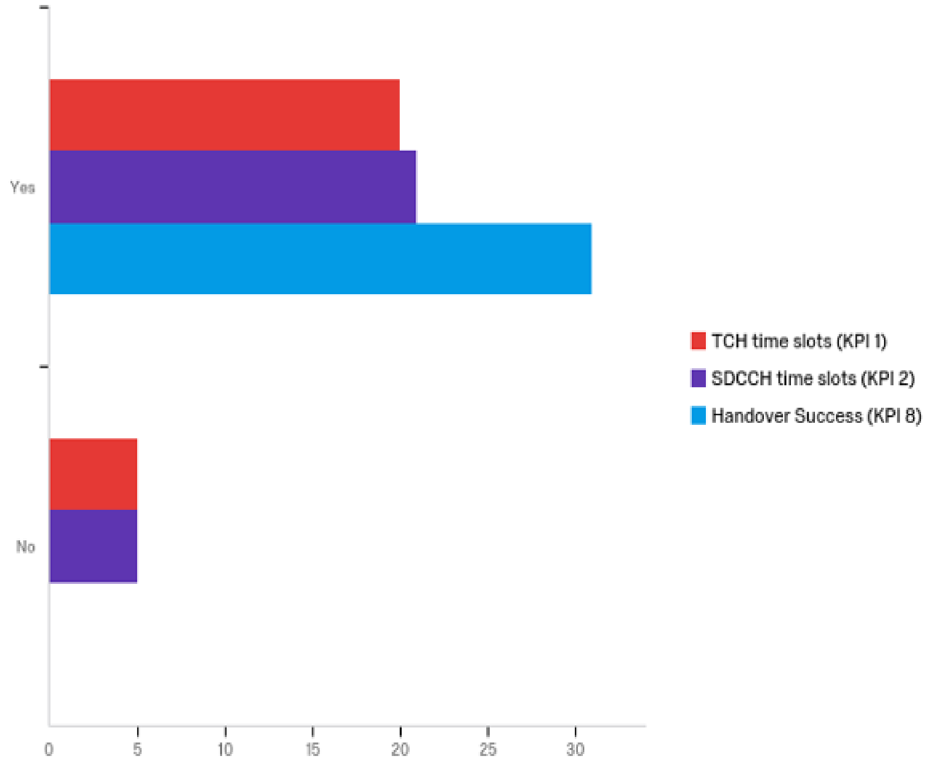
Q3-1 - Are these KPIs appropriate to measure of the BTS's retainability and the ability to continue providing the service?



Q3-2 - If you think that there are other KPIs or you have comments and concerns about the listed KPIs, please provide it here.

the above are not clear KPI what is mean by TCH time slots is it number of active slots / total number of assigned since retain ability is measure as how can the BTS retain the serves from the costumer prospective . also what is mean by TCH Success/ ?? is it the percentage of successes of tch assigned . if it is its not belong to retain ability if its mean the call drop in TCH its can be belong to retain ability
Call drop rate can be check for the retainability
HO success rate
You may consider the hand-off / hand-over KPIs in 'retainability' as these KPIs are important in continuing to provide service.
TCH drop rate SDCCH drop rate
add drop call rate
Tch Drop
Drop rates are also relevant to retainability I would assume.
In this case, I think all are important.

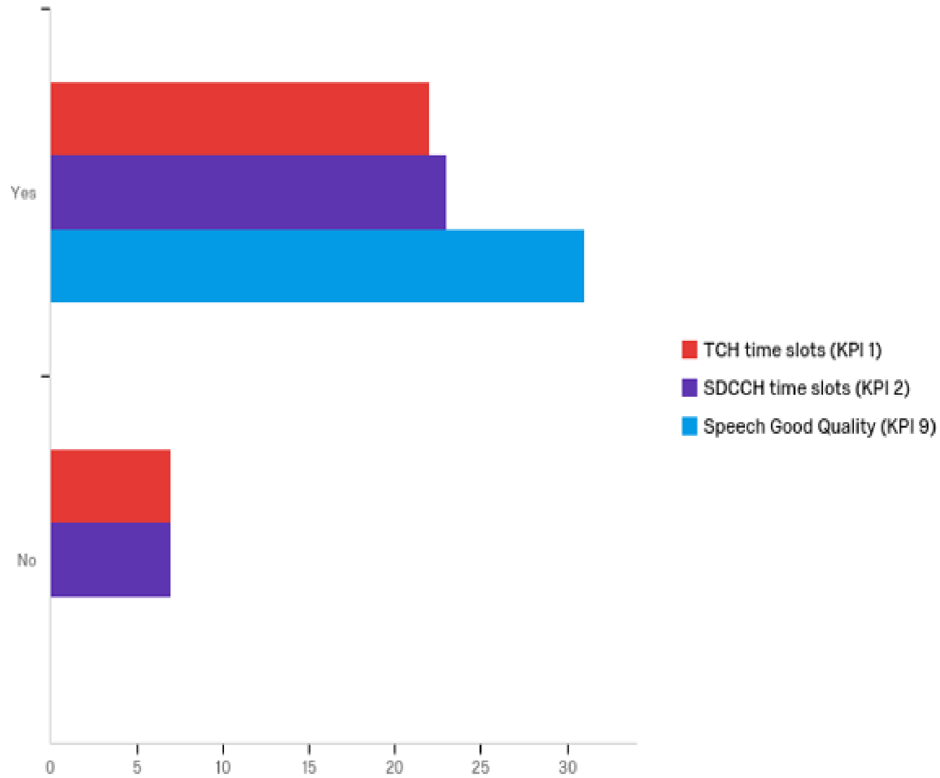
Q4-1 - Are these KPIs above appropriate to measure of the mobility and the fluency of handover calls while customers are moving from and to the BTS?



Q4-2 - If you think that there are other KPIs or you have comments and concerns on the listed KPIs, please provide it here.

enough KPIs, it is ok if there is no Inter-frequency Handover for two bands network
Does handover include handoff? Typically, handover refers to sector/sector handoff while 'handoff' refers to bts to bts hand off.
None
add ping pong effect
In this case, I would ask again how to measure success or failure when handover. BTS-Origin vs BTS-Destination. Additionally, when doing the handover, I think signaling is more important than the voice channel.

Q5-1 - Are these KPIs appropriate to measure the service integrity, which represents the quality of speech during the calls?



Q5-2 - If you think that there are other KPIs or you have comments and concerns about the listed KPIs, please provide it here.

Speech Good Quality for UL Speech Good Quality for DL
Call setup time can be extracted to define a KPI
I'm not as familiar with GSM as I am with CDMA/LTE/etc. Does GSM have a BER or FER metric? I'm assuming speech good quality is a measure of bit error or frame erasure error.
None
Here try to focus on subscriber point of view and operational one.
I think, to measure the service integrity, the "amount" of channels is not significant. The number of channels (Signaling or voice) should be used to measure the congestion. Maybe the use of "integrity" is what makes me think about a different meaning.

Q6 - If you have any comments and concerns on overall research and the models, please provide it here.

If you have any comments and concerns on overall research and the models, please provide it here.
if its possible to involve THE ROI of the BTS as financials parameter in the calculation of efficiency
Most important KPIs were covered in this model, for any further details and KPIs values in the real life of the network do not hesitate to contact us.
Most operators will deploy GSM in 2 bands (900 & 1800 in Europe) interband HO and setting network priorities may play an important role in predicting output KPIs
Do you have any 'call drop' metrics to add as KPIs or 'cell busy/blocked' KPIs? These might be worth adding if you have access to these metrics.
Good
Willing the best for you
ma y be you can add electrical power usage \ site location Rent
as i commented in first page, we are talking about 2G service only where the BTS serve more than one technology
very good and easy to give overview about 2G main KPIs, good job, wish you all the best Tarek
Wish you all the best dear Mauloud.

Touchpoint