Data Service Efficiency of Mobile Network Operators using Data Envelopment Analysis

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ABSTRACT OF THE
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The ubiquity of mobile devices such as smartphones, tablets, laptops, and mobile routers drive unprecedented mobile data traffic year after year. However, the actual mean mobile data usage (volume) per subscriber varies significantly between Mobile Network Operators (MNOs) and countries. Understanding these differences is important for both MNO's evolving business models and telecom regulation in general.

A potential driver for these differences is MNO efficiency in delivering mobile data services. Where efficiency is measured relative to non-financial inputs (subscribers and spectrum) and output (total data volume). Given this context, this study estimates and analyzes the efficiency of data service delivery (data usage by subscribers) of 94 mobile operators from 28 countries by using the Data Envelopment Analysis (DEA) method.

The study demonstrates that many countries have a single highly efficient MNO due to that MNO's effort to gain market share. While in a few other countries all MNOs are high efficiency likely due to country-level initiatives. Furthermore, major economic disparities between countries highly influence country-level efficiency scores. Finally, a case study between Finland and India highlights their similar high-efficiency scores but very dissimilar data service markets.

Keywords: Mobile network operator, Data volume, Data envelopment analysis, Efficiency

Preface

This master thesis has been worked at the Department of Communication and Networking of Aalto University and the work was supported by a thesis grant from the Foundation for Aalto University Science and Technology. The thesis outcomes were presented at the 30th European Conference of the International Telecommunications Society (ITS2019), Finland.

I would like to express gratitude to professor Heikki Hämmäinen for his support throughout the thesis process. Especially the discussions had with him helped me a lot to investigate the economics and business aspects required for the study. I owe my thanks to my thesis advisor Benjamin Finley for his great support in every aspect of the thesis irrespective to the kind of help needed from him. His work on detail approach motivated me to work on the research effectively.

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Manohar Bayyapu Reddy

Contents

Abbreviations

1G	First Generation
2G	Second Generation
3G	Third Generation
3GPP	3rd Generation Partnership Project
4G	Fourth Generation
5G	Fifth Generation
AE	Allocative Efficiency
APEC	Asia-Pacific Economic Cooperation
CDMA	Code Division Multiple Access
CCR	Charnes-Cooper-Rhodes method
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DL	Downlink
DMU	Decision Making Unit
DRS	Decreasing Returns to Scale
EE	Economic Efficiency
EFIS	ECO (European Commissions Office) Frequency Information System
ETSI	European Telecommunications Standards Institute
EU	European Union
FICORA	Finnish Communications Regulatory Authority
GB	Giga Bytes
GDP(PPP)	Gross Domestic Product(Purchasing Power Parity)
GSMA	Groupe Speciale Mobile Association
ICT	Information and Communications Technology
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
IP	Internet Protocol
IRS	Increasing Returns to Scale
ITU	International Telecommunication Union
KPI	Key Performance Indicator
LTE	Long Term Evolution
LTE-A	LTE-Advanced
M2M	Machine-to-Machine
MA	Mergers and Acquisitions
Mbps	Mega Bits Per Second
MHz	Megahertz
MIMO	Multiple Input Multiple Output
mmWave	Millimeter Wave
MNO	Mobile Network Operator
MTC	Machine-Type Communication
OECD	Organisation for Economic Co-operation and Development
PB	Peta Bytes
QoS	Quality of Service

RTS	Returns to Scale
SFA	Stochastic Frontier Analysis
SE	Scale Efficiency
SIM	Subscriber Identity Module
TE	Technical Efficiency
TRAI	Telecom Regulatory Authority of India
UL	Uplink
USD	United States Dollar
VoLTE	Voice over Long Term Evolution
VRS	Variable Returns to Scale
Wi-Fi	Wireless Fidelity
WiMAX	Worldwide Interoperability for Microwave Access

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1 Introduction

The first hand-held mobile phone was introduced in 1973, since then there has been rapid advancement in the innovation of mobile phones and its communication technologies. The growth of cellular devices and their advanced technologies also bringing the demand for more and more mobile data across the world. Many factors are supporting this demand including rapid commodification, adoption of smartphones along with the rapid growth of mobile applications, development of IoT and connected smart home devices. Specifically, Ericsson estimates that by 2023 global mobile data traffic will increase seven-fold compared to 15EB/month in 2017 [2]. However, this data traffic/usage is not equally divided across nations or operators. For instance, in 2017 the average mobile data usage per subscription per month in OECD countries was 2.94 GB, with the highest usage of 15.45 GB in Finland and lowest usage of 0.72GB in Slovakia (see Figure 1) [4]. Consequently, even within a single country, such as Austria, differences between mobile network operators (MNOs) can be substantial. For three Austrian operators the usages are 15.4 GB, 4.69 GB, and 3.4 GB in 2017.

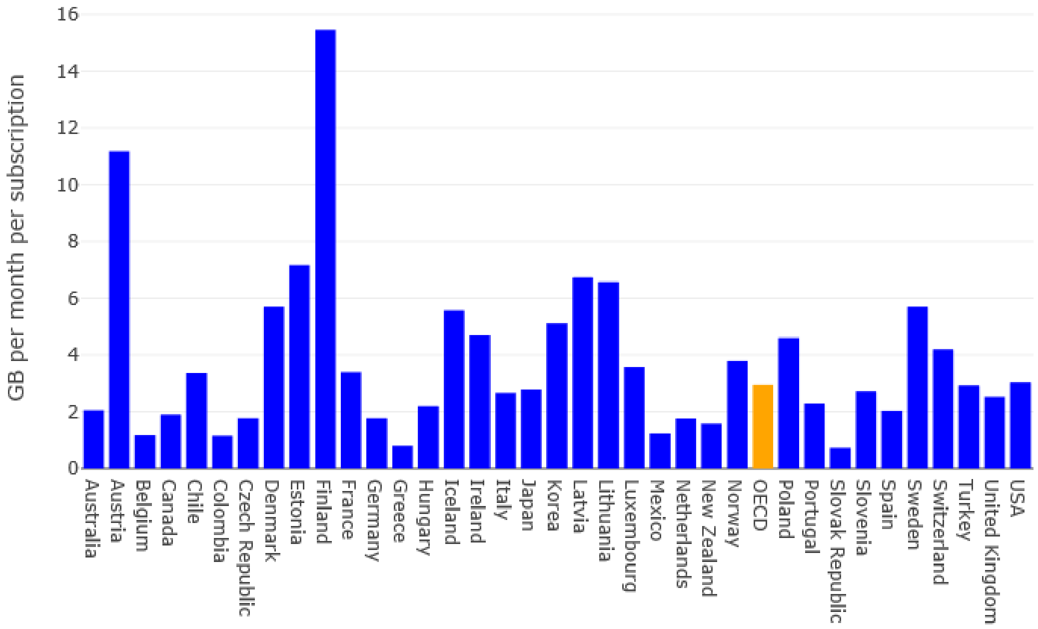


Figure (1) Mobile broadband data usage in OECD countries in 2017.

Even though mobile data usage is rapidly increasing worldwide, huge disparities have been seen in its usage across the nations and MNOs. Understanding the reasons behind these differences is important for MNOs evolving business in ever-changing mobile technologies and the effect of telecom regulations on it. There is a need for the comparison between MNOs operations and resources utilization to find out these reasons. For this purpose, there is a need for the assessment of relative performance between MNOs. Further, this approach helps to find the differences at the country level where one can appraise the impact of regulatory policies.

Performance assessment is an elemental building block of competitive edge and has gained higher attention over the past years. Generally, organizations use performance measurement systems for the reflection of their operations on the current environment and strategies. But this approach could be applied to find the differences in their service delivery by using the associated resources in it. One such approach is measuring the efficiency of the service which is an illustrative indicator in assessing business performance. Efficiency is based on an organization's performance relative to the organization's deployed or utilized resources to achieve that performance. In this context, the data envelopment analysis (DEA) method is a frequently used non-parametric approach to assess productive efficiency with multiple inputs and multiple outputs.

Conventionally, organizations have been estimating their performance through account-based indicators or resources. The conventional performance measures with financial indicators would furnish small support to the firms which are interested in a complete scenario and looking for a higher competing advantage. Thus, there is an importance of using non-account based measures as well. This thesis study is in technical nature and non-financial measures will help for finding the differences in mobile data service delivery. Consequently, non-financial resources involved in mobile data service are used to determine the efficiency scores of MNOs and countries by adopting the DEA method. Further, this approach will illuminate the reasons for high dissimilarities in mobile data usage or mobile data service delivery.

1.1 Research question

Since the inception of 3G technology, the importance of mobile voice services shifted to mobile data services. Accordingly, the MNOs business dynamics and regulatory policies have also changed. The mobile data usage is ever-growing from 4G technology to upcoming 5G technology. However, the differences are quite high in mobile data delivery and usage across the MNOs and countries. Thus there is a need to envisage the reasons behind these dissimilarities which provides to understand MNOs operations and find the success of the regulatory policies in mobile data services. In this regard, the thesis study addresses the following research questions:

- What are the main factors that contribute to significant variation in delivering mobile data services to subscribers at the operator level and country level?
- How the observed factors could be explained in MNOs business operations and strategies along with the regulatory bodies role?

1.2 Scope of study

In general, widespread factors contribute to high variability in mobile data usage such as customer requirements and usage patterns, time spent on the internet, the role of data-hungry applications, dominance of fixed-line broadband, deployment and adaptation of latest mobile technologies, affordability of data services, market dynamics, MNOs business strategies, MNOs resources usage, socio-economic differences, regulation policies and country initiatives towards ICT evolution. There are two observations can be seen from these factors.

- Firstly, these factors can be broadly viewed as in consumers usage, MNOs operations, and regulatory implications. Where, customer usage patterns allow to envisage the differences by their behaviors, demographics and social analytics; these, in turn, help MNOs to implement the strategies in highly competitive market place [52]. Additionally, MNOs operations, specifically apprehending their operational performance would permit to know broader aspects of influencing factors in the delivery of mobile data usage. Further, the regulatory implications facilitate fair competition and fair service levels towards the growth of the telecommunication industry. As the differences in mobile data usage can be seen majorly in three aspects, the MNOs role is a central part in it.
- Secondly, these factors constitute a huge number of variables. Accommodating all these variables is quite challenging in an empirical study due to its data availability and suitability for performing empirical studies.

Thus, in this study, the scope is limited to find the reasons by measuring the efficiency of MNOs with the variables associated with the MNOs non-financial resources used for mobile data services. The efficiency scores are measured by using a non-parametric empirical method called data envelopment analysis (DEA). Few other variables are also considered later in the analysis part to validate the conclusions made.

1.3 Research method

The thesis comprises research based on the empirical results (efficiency scores) obtained from the performance and benchmarking quantitative model. This model widely used in operations research. The data required to conduct the empirical method are obtained from various sources, which are mostly publicly available and followed the external secondary data collection process. These sources are described in detail in chapter 4. Besides, this research also includes literature studies of academic and industry research publications for better implementing the method and analyzing the results with respect to the business strategies of MNOs and underlining regulation policies involved.

Empirical studies are done using DEA method. This method is based on linear programming and can handle multiple inputs and outputs to find the productive efficiency of a firm. This thesis adopts the classical CCR model for finding the efficiency scores of MNOs [18].

1.4 Thesis structure

After initiating the topic, research question and research method in chapter 1, the rest of the thesis is organized into five chapters. Chapter 2 describes background information about production theory concepts, its relation to the efficiency measurements and available methods for the performance assessment of a company. It also discusses the efficiency studies used previously in telecommunications. Chapter 3 explains about the DEA empirical method and related models applied in the thesis for assessing the performance. Chapter 4 deals with the availability, collection, and processing of data that needed to conduct the empirical methods. Besides, it also involves variables selection and software packages available to perform the DEA method. Chapter 5 discusses data analysis and empirical findings from the DEA method to asses the data service efficiency scores of MNOs. Chapter 6 discusses the conclusions of the research and future work.

2 Literature review/Background information

This chapter details the importance of performance assessment, fundamental production theory concepts to understand the performance measurement techniques, various types of efficiencies involved and approaches to calculate these efficiencies to asses the performance. Further, the literature survey explains the importance and application of performance techniques using non-financial parameters and performance techniques used in the telecommunications industry.

2.1 Performance assessment

Performance assessment is the key to the growth of any firm in an industry. There has been a great opportunity of effort for the process of counting, measuring and comparing the performance levels of businesses. It is always important to choose an appropriate performance measurement technique when one intends to measure how well an organization is performing.

Performance denotes to output produced, and results are generated from products, operations, and services that allow assessment and analogs relative to targets, prior outcomes, and other establishments. This could be articulated in both financial and non-financial terms. In continuation, the evaluation of performance is a measurement which quantifies the input and output; performance magnitudes products, operations, services, and complete organization outcomes. This also includes evaluating numerical information with other industries. It is common to illustrate the performance of production units as being more or less “productive”, or more or less “efficient”.

The terms productivity and efficiency are used synonymously to each other in many instances to discuss the performance assessment. Whilst they are closely related, they are two distinct concepts. Productivity is described as the proportion of output units created to input units utilized, whereas efficiency refers to an optimal observed value of productivity. This suggests that efficiency is considered as a relative performance measure in contrast to productivity. The efficiency also depends on how one describes or calculates it for the optimal performance value.

The performance is treated as a suitable mix of efficiency and effectiveness in service industries [50]. Efficiency refers to improving the productivity of a given number of outputs by using the minimum number of inputs, whereas effectiveness refers to the ability to set and achieving the organization’s goals and objectives to perform the job right. As one can see these are separate entities, for an organization they are closely related. The trade-off between usage of both entities together depends on the objectives of a business.

Figure 2 explains the conceptualization of service performance. Applying it to MNOs performance in mobile data services, improving the efficiency would lead to

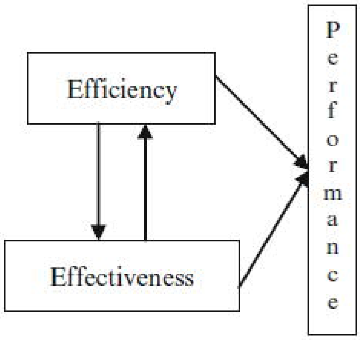


Figure (2) Performance components [50].

data service performance while keeping the constant resources usage, technology-mix (different versions of 3G to 4G technologies) and case-mix (provision to different user segments) with respect to the company's objectives. Effectiveness, more particularly, assesses the outcomes or goals of data services and can be influenced by the efficiency or can affect the efficiency. The effectiveness motivates to check the necessary inputs are being utilized to generate the best post possible outputs. An MNO can be efficient but not effective or vice versa, the motive is maintaining both.

In a mobile data service perspective, the MNOs performance needs to be calculated and compared for many reasons, comprises of:

1. Determining how firms are operating relative to competitors in a given industry sector, often this process also called "benchmarking".

2. Finding the changes in operations from one time period to another time period.

3. Assimilating with public policies.

In this thesis, performance is examined as a relative phenomenon between the MNOs. For this, MNOs are benchmarked at one period of time for the year 2017 in their mobile data services delivered. Also, the regulatory policies that are affected the MNOs operations are analyzed. There are challenges in yielding the effectiveness score as it is related to the firm's objectives. Therefore, the performance study is limited to measuring the efficiency scores.

2.2 Production theory

As already discussed, productivity and efficiency terms are related to fundamental measures for an organization's performance. The performance measuring techniques are related to production theory concepts. In this sub-section, production theory has been used as a framework for describing how different performance measures of a firm can be explained and/or understood.

In general, a production process is the transformation of inputs into single or multiple outputs. This makes to increase the consumer usability of goods and services. The productive resources that a firm utilizes to generate the goods and services are called inputs, and the amount of generated goods and services are called outputs. Generally, inputs are raw materials, labor and capital and outputs are any kind of finished products.

A firm can often select one of the several mixtures of inputs to produce given output volume. A production function is a mathematical depiction with diverse recipes of input-output combinations from which a firm can pick to set its production function. In specific, the production function says about the firm's maximum output quantity yielding from the employed input quantities. If x_i is the ith input and y is the single output, then production function with k inputs represented as

$$y = f(x_i) = f(x_1, x_2, \dots, x_k) \tag{1}$$

This production function is depicted in microeconomic theory concepts. Using this function, one can show the generated maximum output of a firm with the inputs used. However, it does not give findings of whether a firm is efficiently producing that output. It just connotes the inputs combinations to produce the output quantities. Given this drawback with productivity principle, efficiency concept is helpful to find whether the generated output is maximum or not with the used input-output combinations.

Production function can be represented graphically. Figure 3(a) shows a curve of the production function with one input and one output. This explains the law of diminishing returns, which is the most fundamental principle of economics [55]. This serves as a pivotal part in production theory. Law of diminishing return pertains to short-run due to only then is some factor fixed. Under this law, as the firm adds more and more input units it will generate few and fewer outputs. Alternatively, the amount of input increases the marginal product of each unit of input will diminish. Ideally, the firm's production with one input and one output combination will not be the case under study. Consequently, Figure 3(b) and 3(c) show the graphical representation of production function for the two-input and one-output case and one-input and two-output case respectively. Further, extending the graphical representation for a multiple-input and multiple-output case is difficult because of the complexity in drawing the diagrams in more than two dimensions.

Mostly, the production function is defined in the long run on the basis variable productive factors (inputs and outputs). In the long run, all these factors are not fixed and become variable. Thus, the concept of returns to scale (RTS) arises under the circumstances of production function and it articulates the behavior of a production function when the changes occur in all the productive factors. Fundamentally, RTS explains the behavior of variations in output proportion to the variations in the

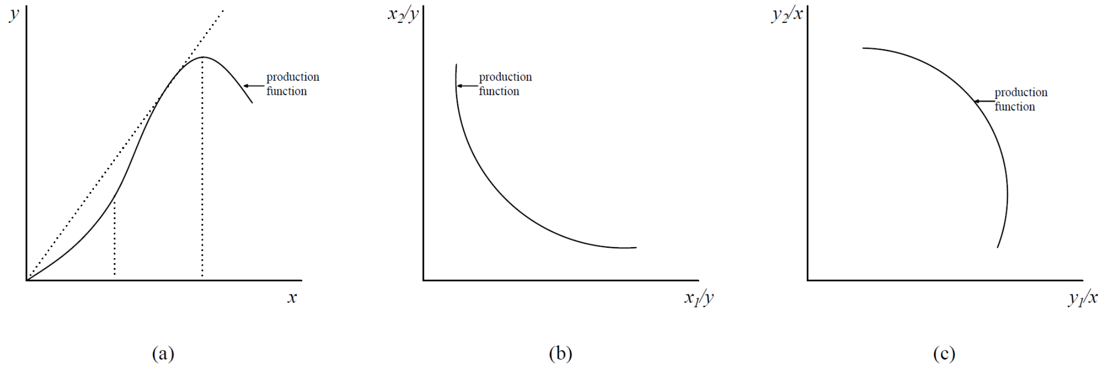


Figure (3) Basic production functions with different input-output combinations.

proportion of input.

There are three different types of RTS principles.

1. Increasing returns to scale (IRS): This is a scenario where the variation in output proportion is higher than to the equi-proportional change in the inputs of production. For instance, if all the inputs are doubled in production then the corresponding output of production increases at more than double rate.

2. Constant returns to scale (CRS): This is a scenario where the change in output proportion is the same as the change in inputs proportion of production. It means if all the inputs quantities are doubled then the output also increases double.

3. Decreasing returns to scale (DRS): This is a scenario where the variation in output proportion is smaller than to an equi-proportional change in the inputs of production. It is also called as diminishing returns to scale. For instance, if all the inputs are doubled then the output increases at lower then double rate.

Figure 4 represents the production function form of all the three RTS principles for a single input and single output case.

The technical relationship between inputs and outputs are referred widely as production function in economics literature, whereas it is referred to as production frontier in efficiency measurement literature. However, these two phrases can be used interchangeably [20]. This is the key connection between economic theory literature and efficiency measurement literature. The frontier term widely uses in the latter research area. Thus production frontier is used in most parts of this thesis.

2.3 Efficiency measurement concepts

Figure 5 illustrates the complete framework associated with performance assessment. Efficiency is only one part of performance assessment and its measurement is a prime

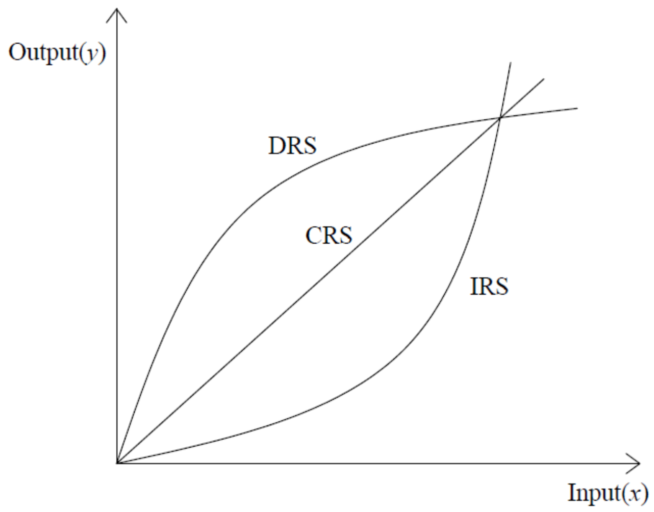


Figure (4) Production function for all three RTS principles.

objective in this research (also discussed in section 2.1). Further, the efficiency is divided into two concepts and it is important to describe these two concepts which are shown in Figure 5. The discussion of efficiency measurement concepts starts with seminal work of Farrell in 1957. This work is based on the simple estimate of firm efficiency with multiple inputs which was proposed by Debreu and Koopmans [27]. According to Farrell's work, an organization's efficiency comprises of two parts: one is technical efficiency, this contemplates efficiency of an organization to acquire the maximum output with provided inputs, and second is allocative efficiency, this envisages the use of optimal proportions of inputs with the specified costs of these inputs and production technology. The mixture of these two efficiencies is called as economic efficiency [20].

Allocative and technical efficiencies are calculated in a couple of approaches viz., input-oriented and output-oriented. The former one (input-oriented) addresses the reduction of input supplies needed without altering the output volumes. In contrast to this, the latter one (output-oriented) offers to expand the output quantities by keeping the input quantities constant. The following sub-section starts with a focus on reducing the inputs, which is Farrell's fundamental idea and this is termed as input-oriented measures. The subsequent sub-section to this is focused on output-oriented measures.

2.3.1 Input-oriented

Consider a firm delivering only one output y with the use of two inputs x_1 and x_2 with a postulate of constant returns to scale (CRS). The firm's production frontier is $y = f(x_1, x_2)$, it could be inscribed as $1 = f(x_1/y, x_2/y)$ due to characterization of

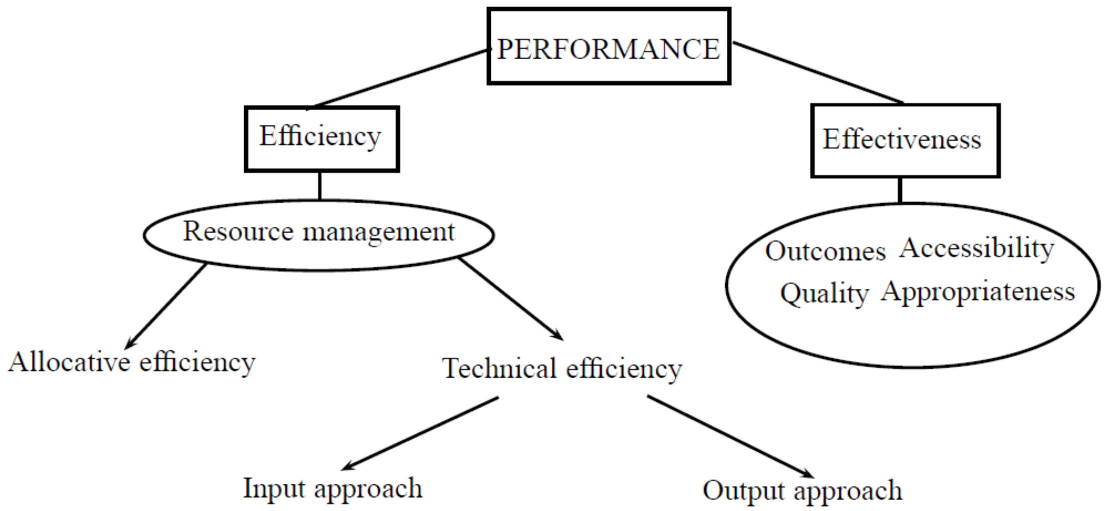


Figure (5) Framework for performance assessment[53].

CRS principle. Thus the production frontier could be expressed as a unit isoquant and this is represented in Figure 6 as FF'. The FF' represents the produced output unit with a minimum mixture of inputs per output unit. Consequently, supporting this, the combination of inputs that fall on unit isoquant is deemed technical efficient. Conversely, if a point falls over the isoquant such as point P which uses more than enough resources to produce an output unit thus this point is defined as technical inefficient. From Figure 6, the distance QP across the line OP estimates a production unit's technical inefficiency at point P. This span indicates all the quantity of inputs can be divided instead of reducing output quantity. The technical inefficiency incorporated with the production unit at point P expressed by QP/OP, and hence, the production unit's technical efficiency (TE) is 1-QP/OP or OQ/OP.

Technical efficiency calculated as

$$TE = OQ/OP \tag{2}$$

The producer is accountable not only for choosing a technical efficient point on the isoquant but also for choosing the optimal point to minimize the cost. This is an allocation problem and the related efficiency is called as allocative efficiency (AE). It is also referred to as price efficiency in economic literature. For instance, here cost minimization is assumed by knowing the market prices information, the input price ratio is depicted by isocost-line AA' as shown in Figure 6. In this instance, the least-cost combination of inputs represented by point Q' which is technical and allocative efficient but the combination of the inputs represented by Q is technical efficient but not allocative efficient. It demands producer to move from Q to Q' for the cost reduction.

The allocative efficiency associated with the producer at point P is

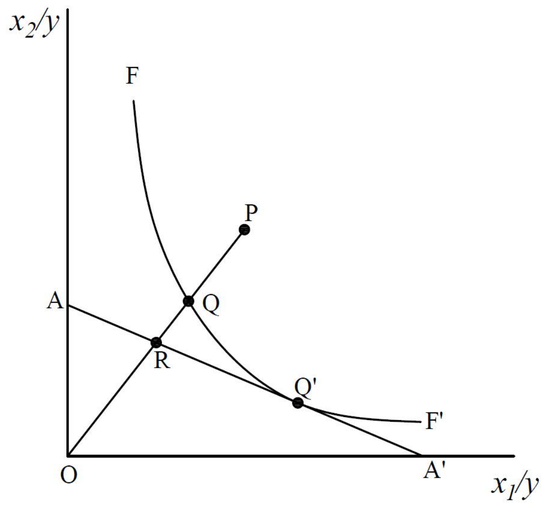


Figure (6) Technical and Allocative efficiencies in the input oriented approach. [27]

$$AE = OR/OQ \tag{3}$$

The technical efficiency and the allocative efficiency could be defined jointly as overall efficiency (OE) [27]. Later this term renamed as economic efficiency (EE) in the literature [49]. It is expressed as

$$OE = EE = TE * AE = OQ/OP * OR/OQ = OR/OP \tag{4}$$

2.3.2 Output-oriented

The above input-oriented model estimates efficiency with the proportionate decrease of input amounts without altering the output amounts produced. In contrast to this, one can alternatively look into the proportionate increase of output amounts without altering the input amounts utilized. This is called as output-oriented measures and present section illustrates the same.

Here, a production with y_1 and y_2 outputs and x inputs are considered to illustrate the output-oriented efficiency. Under the constant returns to scale (CRS), the unit production frontier of chosen production is represented by curve EE' and producer at point A represents an inefficient one which lies below the curve. Applying the Farrell's principles the same as in the input-oriented case, distance AB marks the inefficiency. The technical efficiency in this case is

$$TE = OA/OB \tag{5}$$

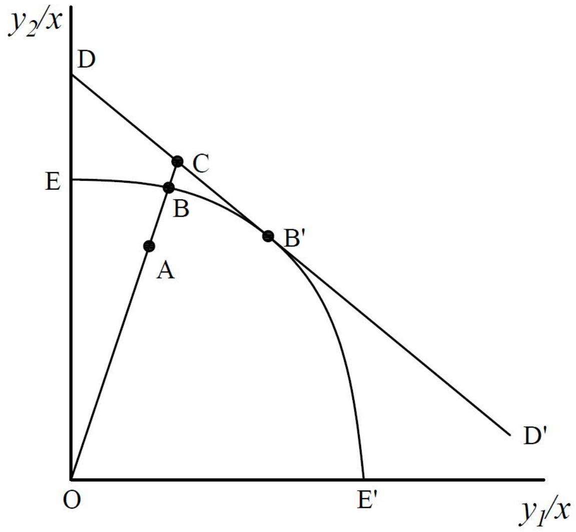


Figure (7) Technical and Allocative efficiencies in output oriented approach.[20]

In the event of output-orientation, a producer needs to choose the optimal point to maximize the revenue along with the technically efficient. In this case, output price shown by line DD' in Figure 7. The allocative efficiency associated with the producer at point A is calculated as

$$AE = OB/OC \tag{6}$$

The overall efficiency or economic efficiency in the output-oriented case is

$$OE = EE = TE * AE = OA/OB * OB/OC = OA/OC \tag{7}$$

2.4 Approaches for measuring the efficiency

Efficiency is the best feasible outcome of a decision-making agent by comparing all the perceived outcomes. The input-oriented and output-oriented approaches are explained in subsections 2.3.1 and 2.3.2 which facilitate to calculate technical efficiency and allocative efficiency. Consequently, these two efficiencies can be used to estimate economic efficiency. Calculation of these efficiencies consists of evaluating the concealed production frontier. Further, the efficiency measurement requires a relative comparison of the actual performance of an individual production unit with an optimal performance observed on the appropriate production frontier. This frontier is not an ideal one and varies according to the production units and its associated parameters considered in the study. Since this production frontier is not known, an empirical approximation is required. Thus, an elemental production frontier can be calculated empirically in distinct methods. These empirical methods are parametric and non-parametric. The parametric method follows an economic model and it's counterpart non-parametric method follows a mathematical model. These methods use distinct methods to handle the data for enveloping which majorly helps for dealing with random noise and flexibly structuring the production unit. Thus both contradict in several modes but benefits concerning one on another bring out two characteristics [53]:

- Firstly, the econometric approach is stochastic in nature which accounts to differentiate the noise and inefficiency effects, whereas mathematical approach (precisely linear programming approach) is deterministic in nature and incapable to factor out the noise and inefficiency.
- Secondly, due to the econometric approach is parametric in nature which makes the result to suffer from a wrong selection of functional form, whereas programming approach is non-parametric and unsusceptible to functional form.

In this section, the prominent and widely used methods that exist in the parametric procedure (stochastic frontier analysis) and non-parametric procedure (data envelopment analysis) are explained concisely in sub-sections 2.4.1 and 2.4.2.

2.4.1 Stochastic frontier analysis (SFA)

Stochastic frontier analysis (SFA) is one of the frequently used parametric technique. The basis of SFA was developed from the seminal articles of Meeusen and van den Broeck [47] and Aigner, Lovell and Schmidt [8] in the year 1977. Since then, the research in this area have been producing many reformulations and extensions of the original model.

The basic idea of SFA is motivated by the deviation of any firm being studied from the production function frontier. This deviation might not be fully in the firm's control. For instance, the external factors such as random failure of equipment or extreme weather conditions might lead to the firm's efficiency understudy in deterministic frontier models. Further, any error in the model or its variables measurement including output could also lead to increased inefficiency.

The SFA's pertinent mathematical formulation is [29]

$$y_i = f(x_i) TE_i e^{vi} \tag{8}$$

where TE_i is technical efficiency of ith of N firms in a sample of measurements, v_i is statistical noise or measurement error. The below equation is reformulated from the above by including measurement errors, statistical noise and random variation across all the firms. This equation is the log-linear specification of the stochastic production function.

$$lny_i = \alpha + \beta^T x_i + v_i - u_i = \alpha + \beta^T x_i + \epsilon_i \tag{9}$$

In equation 3, x_i is a inputs vector, α and β are technology parameters. ϵ_i is the composed error with v_i as measurement error and specification error and u_i as inefficiency parameter. The measurement error v_i is represented as normally distributed disturbance $\mathcal{N}(0, \sigma_v^2)$[15]. The inefficiency factor u_i modelled as half-normal distribution $\mathcal{N}^+(0, \sigma_u^2)$ [8] or exponential one $\epsilon(\sigma_u)$ [47] in the fundamental SFA models.

2.4.2 Data envelopment analysis

In stochastic frontier analysis (SFA), the validity of production function frontier as the performance evaluation of observed input-output bundle vitally influenced by the relevance of the functional form used in the model. The choice of the desired function form is subjective and driven by mathematical easiness and controllability. Moreover, the selection of the half-normal or exponential stochastic distribution depends on analyst preference. In contrast to this, the DEA method is non-parametric needs no parametric production frontier and depends on basic production technology with a few common assumptions. The basic method introduced by Charnes, Cooper, and Rhodes (CCR) in 1978 based on the seminal effort of Farrell [18] and this method further generalized by Banker, Charnes, and Cooper (BCC) in 1984 [11]. It uses observed actual input-output data and the assumptions to deliver an efficiency measure, by which firms efficiencies can be compared.

The transformation of input bundle x into output bundle y of any production technology represented by production possibility set

$$P = \{(x, y) : yproducedfromx; x \geq 0; y \geq 0\} \tag{10}$$

For one output case, for any input bundle x^0, $f(x^0)$ can produce the maximum quantity of y and the production function is given as

$$f(x) = max(y) : (x, y) \in P \tag{11}$$

In this case, an equivalent production possibility set would be

$$P = \{(x, y) : y \leq f(x); x \geq 0; y \geq 0\} \tag{12}$$

This production possibility set able to give the quantities of input and output bundles of the given production technology to be measured. According to the traditional DEA models, all observed production possibilities are feasible. This is one of the fundamental assumptions in these models. Thus, this DEA approach does not permit any statistical noise or error and the proper care needed to select the inputs and outputs and collection of related data.

In this thesis, the DEA method is considered as the main performance assessment method. Hence, this method is explained in detail in chapter 3.

2.5 Performance measurement with non-financial parameters

As discussed in section 2.1, it is necessary to evaluate the performance with operational related characteristics to asses or enhance the operations of any system. These characteristics can be divided broadly into financial characteristics and non-financial characteristics. Particularly, the performance evaluation is complicated due to the problem of selecting the relevant operational characteristics and measurement of these with different scales and units [26]. This problem can be handled by the DEA method as it works on "unit invariance" property. This facilitates or gives freedom to choose the inputs and outputs irrespective of their nature. In general, one believes that the performance of a firm is related to its financial operations. Additionally, this belief strengthens because the literature background of DEA lies on the foundations of economic theory and production theory. Nevertheless, there have been researched studies suggest that non-financial measures also improve the firm's performance. In this section, such research studies literature has been reviewed because this thesis adopts the non-financial parameters for calculating the MNO's efficiency in mobile data service perspective. This section broadly divided into three parts.

Firstly, research studies in the view of the importance of measuring the performance with non-financial measures. Account-based measures have been using to assess the performance of a firm for a long time. But the advent of competitive nature actualities such as quick response to customer expectations, improved customization, flexible to deliverables, quality over price and new manufacturing processes are questioning the adequacy of account-based performance measurement methods [19]. A number of authors highlighted the importance of non-financial elements in the firm's performance [37], [39], [19], [12]. These elements such as quality of the product or service, user satisfaction, and market share have been using by numerous companies to assess and reward managerial performance [37]. Besides, rewards are connected to future financial performance and this is ignited by innovation, quality and customer satisfaction which are the outcomes of managerial actions [39], [31]. Additionally, customer satisfaction is also notably linked with future financial performance [12].

Secondly, performance measurement using DEA with non-financial measures as inputs and outputs. There have been studies where DEA has employed for finding the efficiency of a firm exclusively using non-financial parameters. The studies are related to varied service industries. Dénes et al. used DEA with non-financial measures for finding the performance of rehabilitation departments and explored operational shortcomings in these departments [26]. The non-financial approach followed in another service industry where the performance of Latin-American airline companies measures [17]. In one more study, authors used the DEA method to find the relation between operational technical efficiency of the US airline industry and its stock market returns, where they used non-account based measures [9]. In the telecommunication industry, the DEA method used with non-financial measures related to mobile services quality such as faults, success rate, drop rate, delay, complaints, and subscribers.

Finally, relating the non-financial measures importance and its usage in performance measurement of mobile operators in mobile data services. Mobile operators continued to feel the pressure in generating the revenues [6]. The tremendous growth in the mobile data usage complementing this pressure. According to McKinsey research, mobile data volume has turned into customer's most significant purchasing consideration after the price in the mobile business. After taking out price from the equation, data volume and speed contribute key role in user's buying choice [10]. Given these reasons, this thesis is focused to envisage the performance of mobile operators by using non-financial measures such as data volume and speed involved in data services to answer the research question and objectives that are explained in section 1.1. The studies related to the application of DEA method in the telecommunication industry are reviewed in the following section.

2.6 Efficiency studies using DEA in telecommunications

Nowadays, the telecommunication sector has been facing fierce competition with pressure from both technical advancements and market competition. For the competitive advantage, finding mobile operators efficiency in the telecommunications market is important. Previous research studies have studied the efficiency of mobile operators in the telecommunication industry by applying DEA method. These studies are focused in different areas such as worldwide, economic group level, regional level and national level.

At worldwide, for instance, in a study, the authors compared the ranking of 39 mobile operators that were listed in the 2003 Forbes list with their productive efficiency scores, where results state that Forbes rankings and productive efficiency rankings of mobile operators are not identical [60]. In another study, the authors attempted to find the managerial performance of 36 global mobile operators. In which, these operators grouped based on the regions and learned that operators in the Asia-pacific and America region did perform inferior to operators in Europe. Moreover, the authors found that state-owned firms operated better than the private telecoms [36]. In one more study, 24 Fortune 500 ranked global telecom operators performance was benchmarked using context-dependent DEA method. In which, operator's efficiency scores grouped into various stages of efficiency frontier and further investigated the operating performance [44].

Some studies focused on economic group levels such as OECD, APEC, and BRICS. Few studies used OECD published telecommunications data and calculated the efficiency at country level [28], [43]. In one of such study 30 member states data was used and analyzed the performance in four different groups. Eight countries found efficient ones and concluded the results with finding the requirements needed to improve the efficiency of low performed states concerning with the policy implications [28]. In another study, 24 OECD countries data from 1980 to 1995 was used and found that the competition in the telecommunication industry to be linked with escalated production efficiency [43]. At APEC level, one particular research investigated that efficiency improvement influenced heavily by scale and scope economies, whereas market competition and privatization impact on performance was not at a considerable level. In this study, the authors used 24 telecom firms data for the period 1999-2004 in APEC member economies [34]. In some other study, the authors reviewed the performance of 16 major operators in APEC countries. In this study results shown that higher efficiency achieved by the operators with high penetration rate and efficiency is not related to their revenue and policy implications that were discussed in the paper [42]. In another research work, DEA analysis was performed on ten major operators in BRIC nations to find operational efficiency. In which, authors observed full operational efficiencies achieved by few operators irrespective of differences in their revenue scales [41].

At the regional level, in a study, the efficiency of 17 major MNOs in the Asia-Pacific region was appraised, where authors used the efficiency scores to explore the performance of MNOs in relation with fixed-line penetration. Based on this penetration, they categorized firms concerning with their country of operation as mobile jumping and non-mobile jumping countries. Results indicated that operators with lesser fixed-line penetration achieved total asset efficiency than their counterparts [35]. In another research, the DEA based efficiency analysis considered to inspect the influence of corporate mergers and acquisitions (M&A) on an operator's performance in the Association of Southeast Asian Nations (ASEAN) countries [54]. In one more study, the benchmark of operators was performed in the European region, in which 19 public telecommunications organizations were considered and explored that operational efficiency can be achieved irrespective to the revenue size [51].

When it comes to the country level, a couple of studies scrutinized the performance of Indian mobile operators [46], [48]. In the first study, the authors observed that companies with higher operational efficiency and effectiveness of service accomplished excellent profitability [46]. In the second study, parameters related to the quality of service delivery used and reviewed the performance of Indian operators [48] .

Table 2 lists the summary of research works in the telecommunications domain where the relative efficiency of MNOs was measured. From this, one can observe that most of the studies were based on input-output combinations either exclusive to financial measures or mixed with both financial and non-financial measures. As mentioned in section 2.5, this thesis adopted non-financial parameters to measure the relative performance of mobile operators across the globe. The details are discussed in chapter 4 about input and output selection and its applicability to DEA method.

Table (2) Summary of studies in which DEA methods are used in telecommunication industry.

Title	Method	Inputs	Outputs
Is mobile jumping more efficient? Evidence from major Asia-Pacific telecommunications firms[35]	SBM-DEA	Total assets Labor	EBITDA Broadband Fix-network Mobile
The comparative productivity efficiency for global telecoms[60]	CCR,BCC	Total assets CAPEX Employees	Revenue EBITDA EBIT
A Comparative Study of the Performance Measurement in Global Telecom Operators [36]	CCR,BCC,SE	Total assets CAPEX Employee	Revenue EBITDA EBIT Net income
Comparing operational efficiency of the main European telecommunications organizations:A quantitative analysis [51]	BCC	Access lines Mobile sub. Employees	Revenue
Efficiency of Telecommunication Companies in ASEAN: Corporate Mergers and Acquisitions [54]	CCR,BCC	Current assets Fixed assets	Revenue
Efficiency ranking of the OECD member states in the area of telecommunications:A composite AHP/DEA study [28]	BCC	Access lines Staff Internet hosts	Subscribers Revenue
Competition and production efficiency Telecommunications in OECD countries[43]	CCR,BCC,SE	Telephone lines Staff Investment	Revenue
Efficiency and Productivity of Major Asia-Pacific Telecom Firms [34]	CCR,BCC,SE	Fixed assets Employees	Fixed-line revenue Non-FL revenue
Measuring the technology gap of APEC integrated telecommunications operators [42]	DEA Meta frontier	Employees Assets Capital	Revenue FL sub. Mobile sub. BB sub.
Benchmarking telecommunication service in India: An application of data envelopment analysis [48]	CCR,BCC,SE	No. of faults Call suc. rate Call drop rate Voice quality	Service delay Comp./bills Comp. res. refunds per. No. of sub.
Operational efficiency and service delivery performance: A comparative analysis of Indian telecom service providers [46]	2-stage DEA	No. of BTS Operation cost	ARPU Sub.

3 Data envelopment analysis

In the previous chapter, the DEA method is briefly introduced along with the fundamentals of productivity and efficiency which are base for the frontier methods. DEA method is a non-parametric procedure for data fusion. The prime advantage with DEA is that it can easily blend different types of data into the same dimension comparing with other data fusion methods [22]. Non-parametric means that DEA method facilitates data to fit into a functional form without any statistical, unlike its counterpart parametric technique.

DEA is helpful to assess the Decision-making units (DMUs) performance by finding the relative efficiency. DMU is any kind of production unit for which efficiency need to be evaluated. DMUs of any type with similar variables can be evaluated. Each DMU with different features can be taken into consideration as long as these features can present numerically. Charnes et al. introduced term DMU in 1978 [18]. For instance, in this thesis DMUs are MNOs and countries.

There is a multitude of DEA models are developed by researchers. In which, the CCR model[1] and the BCC model[2] are the two most widely used DEA models. CCR model works on CRS principle and the BCC model uses VRS principle. In the thesis study, CCR model is adopted for finding the productive efficiency of MNOs.

The following sections illustrate how the two available approaches in CCR-DEA model are mathematically structured.

3.1 Input-oriented CCR model

Charnes et al. generalized fundamental productive ratio into multiple inputs and outputs. In which, these inputs and outputs of each DMU formed with the weights v_i and u_r to calculate the productivity ratio

$$efficiency = \frac{output}{input} = \frac{u_1 y_{10} + u_2 y_{20} + \ldots + u_q y_{q0}}{v_1 x_{10} + v_2 x_{20} + \ldots + v_k x_{k0}} \tag{13}$$

A DMU's efficiency achieved as the maximum proportion of weighted outputs to weighted inputs in the CCR model. The calculated ratio of a DMU need to be lesser than or equal to unity and applies to all DMUs in thes study. The optimal weights are obtained from the data and these weights may vary for individual DMU. The above ratio is maximized to determine the weights using fractional programming model

[1]An original DEA model, abbreviated after authors Charnes, Cooper, and Rhodes

[2]one of first major extensions to the original DEA model, abbreviated after authors Banker, Charnes, and Cooper

$$
\begin{aligned}
\max h_0 = & \quad \frac{\sum_{p=1}^{q} u_p * y_{p0}}{\sum_{a=1}^{k} v_a * x_{a0}} \\
\text{s.t.} & \quad \frac{\sum_{p=1}^{q} u_p * y_{pb}}{\sum_{a=1}^{k} v_a * x_{ab}} \quad \leq 1 \;\; b = 1, \ldots, l \\
& \qquad\qquad u_p, v_a \quad \geq 0 \quad p = 1, \ldots, q \quad a = 1, \ldots, k
\end{aligned} \tag{14}
$$

Here, considered l DMUs: $DMU_1, \ldots, DMU_l$ with k inputs: $x_1, \ldots, x_k$ and q outputs: $y_1, \ldots, y_q$. And also, x_{ab} and y_{pb} are b^{th} DMU's inputs and outputs. Additionally, v_a and u_p are the input and output weights (or) multipliers.

The main objective is to find the weights v_a and u_p which maximizes the ratio for a DMU and constraints helps to keep the ratio not to exceed one. The fractional model (9) can be changed into the linear programming model:

$$
\begin{aligned}
\max h_0 &= \sum_{p=1}^{q} u_p * y_{p0} \\
\text{s.t.} \qquad \sum_{a=1}^{k} v_a * x_{a0} &= 1 \\
\sum_{p=1}^{q} u_p * y_{pj} - \sum_{a=1}^{k} v_a * x_{ab} &\leq 0 \quad b = 1, \ldots, l \\
u_p, v_a &\geq 0 \quad p = 1, \ldots, q \quad a = 1, \ldots, k
\end{aligned} \tag{15}
$$

The above model is termed a multiplier model and delivers at least one efficient DMU. This model produces a production frontier with a straight line starts from an origin and passes through on all efficient DMUs in case of one input and one output combination. This creates constant returns to scale situation as input proportional change creates the same output proportional change.

The dual model of (10) expressed as:

$$
\begin{aligned}
& \min \theta - \epsilon \sum_{a=1}^{k} S_a^- - \epsilon \sum_{p=1}^{q} S_p^+ \\
\text{s.t.} \quad & \theta * x_{ao} - \sum_{b=1}^{l} \lambda_b * x_{ab} - S_a^- = 0 \qquad a = 1, \ldots, k \\
& \sum_{b=1}^{l} \lambda_b * y_{pb} - S_p^+ = y_{p0} \qquad p = 1, \ldots, q \\
& \lambda_b, S_p^+, S_a^- \geq 0 \quad b = 1, \ldots, l, a = 1, \ldots, k, p = 1, \ldots, q
\end{aligned} \tag{16}
$$

From (10), as $S_p^+ \geq 0$ and $S_a^- \geq 0$, the first two constraints implicit to $\sum_{b=1}^{l} \lambda_b.x_{ab} \leq \theta.x_{ao}$ and $\sum_{b=1}^{l} \lambda_b.y_{pb} \geq y_{p0}$. This show that entire observations have a large quantity of inputs and small quantity of outputs compared to the point $(\sum_{b=1}^{l} \lambda_b.x_{ab}, \sum_{b=1}^{l} \lambda_b.y_{pb} \geq y_{p0})$ on the production frontier. In this scenario, production frontier envelops all observations. Thus, the model expressed in (11) called as envelopment model.

It is advisable to use dual (envelopment form) model in CCR method [22]. In DEA, generally, the number of DMUs (l) is higher than the sum of inputs and outputs $(k+q)$. Thus, the dual form is easier to solve (with $k+q$ constraints) than the primal (with l constraints). Further, solutions obtained from dual are easy to interpret than the primal solutions. The results from dual also help the inefficient unit to indicate the improvement options.

In this section, the purpose of the CCR model considered as minimizing the inputs while generating at least required chosen output scales. It is termed an input-oriented model. Next section illustrates an output-oriented CCR model.

3.2 Output-oriented CCR model

The calculation of efficiency from the output side is also possible. This technique is called an output-oriented model. The output-oriented model aims for maximization of outputs by utilizing specific quantities of any observed inputs. The efficiency represented as a reciprocal of h_0. The output fractional programming model is

$$\begin{aligned} g_0 = \min \frac{1}{h_0} = & \frac{\sum_{a=1}^{k} v_a * x_{a0}}{\sum_{p=1}^{q} u_p * y_{p0}} \\ \text{s.t.} \quad & \frac{\sum_{a=1}^{k} v_a * x_{ab}}{\sum_{p=1}^{q} u_p * y_{pb}} \geq 1 \quad b = 1, \ldots, l \\ & u_p, v_a \geq 0 \quad p = 1, \ldots, q \quad a = 1, \ldots, k \end{aligned} \tag{17}$$

The primal from output oriented approach in linear programming model as follows:

$$\begin{aligned} \min g_0 = \; & \sum_{p=1}^{q} v_a * x_{a0} \\ \text{s.t.} \quad & \sum_{p=1}^{q} u_p * y_{p0} = 1 \\ & \sum_{a=1}^{k} v_a * x_{ab} - \sum_{p=1}^{q} u_p * y_{pb} \geq 0 \quad b = 1, \ldots, l \\ & u_p, v_a \geq 0 \quad p = 1, \ldots, q \quad a = 1, \ldots, k \end{aligned} \tag{18}$$

And the corresponding dual form or envelopment form:

$$
\begin{aligned}
&\max \phi + \epsilon \textstyle\sum_{p=1}^{q} S_p^+ - \epsilon \textstyle\sum_{a=1}^{k} S_a^- \\
\text{s.t.} \quad & \phi * y_{p0} - \textstyle\sum_{b=1}^{l} \lambda_b * y_{pb} + S_p^+ = 0 \quad p = 1, \ldots, q \\
& \textstyle\sum_{b=1}^{l} \lambda_b * x_{ab} \qquad + \mathrm{S}_a^- = x_{a0} \quad a = 1, \ldots, k \\
& \qquad \lambda_b, S_a^-, S_b^+ \geq 0 \quad b = 1, \ldots, l, a = 1, \ldots, k, p = 1, \ldots, q
\end{aligned} \tag{19}
$$

The constraints in this model depict that it finds for a larger value of ϕ to expand the outputs while keeping inputs at the present position x_{a0}. As explained before, this is the objective of an output-oriented model.

An output-oriented CCR-DEA model is chosen in the thesis study for assessing the productive efficiency of MNOs based on selected inputs and outputs variables. These inputs and outputs selection process is discussed in section 4.2.

4 Research approach

This chapter explains the steps followed towards conducting the DEA method for the empirical analysis. These steps are described in subsequent subsections. These subsections are followed complete research process, inputs and outputs selection, decision-making units selection, availability and collection of data and software availability. In which, thesis process illustrates the overall research methodology followed for the study and indicates where each process is included in the thesis document. The software availability section gives the gist of available packages and direction towards the employed software package for the study. The other subsections describe the methodological concerns involved in data set creation to do empirical analysis.

4.1 Research process

Research involves the process of gathering, analyzing and evaluating data to solve the study objectives. The research qualification depends on the characteristics associated with the process involved in it. The required characteristics by the process are controlled, accurate, methodical, factual and provable, empirical and decisive [40]. Thus, this thesis study is adopted to have all these characteristics in the research process. Further, this thesis is applied research[3] type from the aspect of the application, whereas, it is a blend of descriptive type[4], correlational type[5], and explanatory type[6] from the aspect of objectives.

The positivist paradigm[7] is followed for the study and the research process features both evaluative and descriptive characteristics. For the evaluative approach, the research work depends on mainly statistical analysis and production theory principles. Additionally, the Data Envelopment Analysis (DEA) method is utilized to calculate efficiency scores with selected variables for the study and this method is non-parametric. For the descriptive approach, extensive literature is studied for the textual and numerical data.

Figure 8 illustrates the overview of the research process flow followed in this study. Each step of the process is explained in different chapters of the thesis study and which chapter contains which process is indicated in the flow chart against each process.

[3]the conclusions for the study being intended to use in grasping certain phenomenon/problem or to change the existing scheme/situation.

[4] detailing a condition, circumstance, problem or issue

[5]Initiating or finding a relationship among two or more variables

[6]justifying how some things occur the way they do

[7]a paradigm which emphasizes logical examination through observation, the knowledge gained from human experience, factual information obtained from appropriate measurements, data transformed to quantifiable units for empirical analysis, deductive reasoning, causes effects and outcomes, the importance of replication, generalization which is not by chance [21]

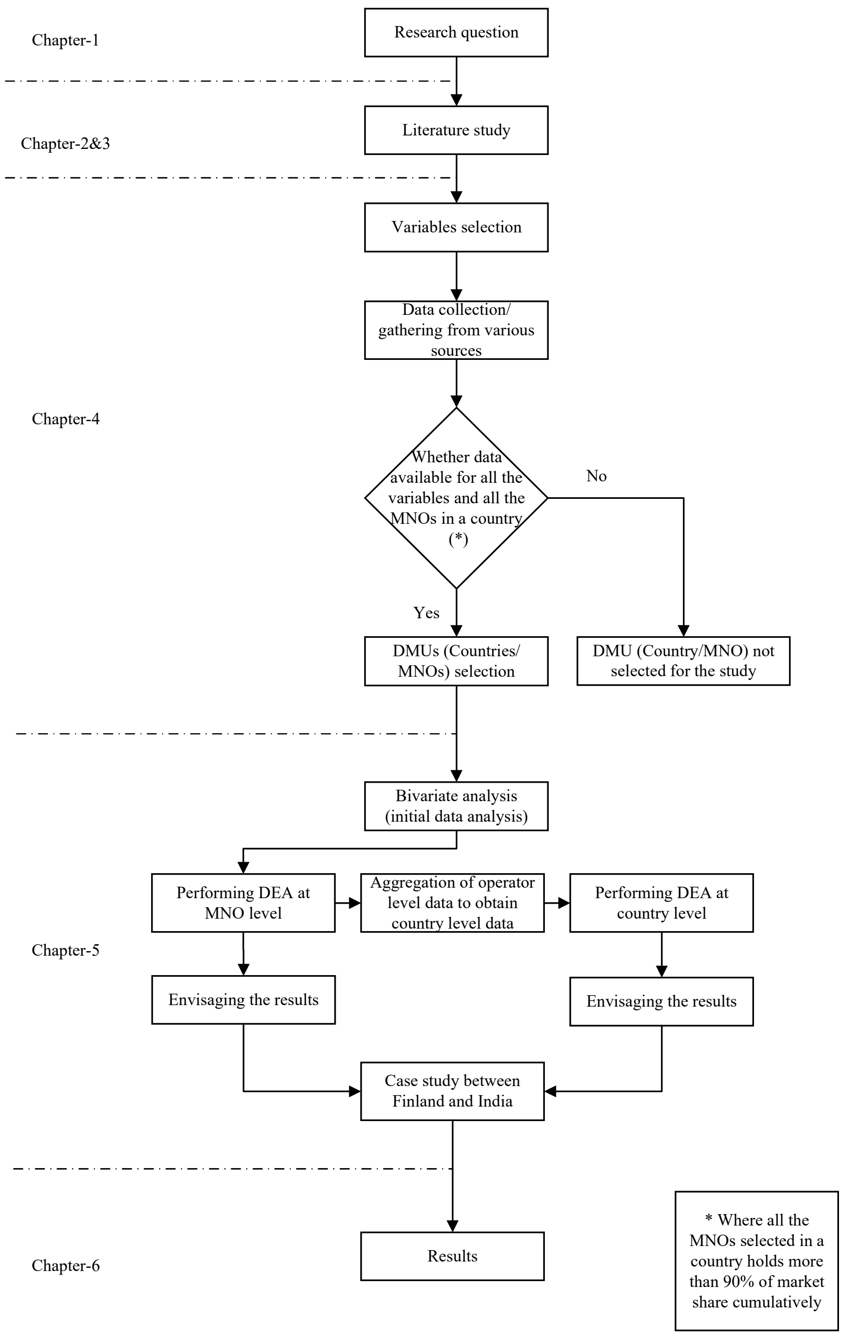


Figure (8) Research process followed in the thesis.

4.2 Variables selection

Variables (inputs and outputs) selection is critical for performing DEA analysis. As the prime objective of this study to envisage differences in mobile data services through performance investigation of MNOs, the selection of inputs and outputs are considered that related to data services delivery. Though many financial and non-financial factors contribute to the performances, this thesis concentrated on accounting the performance view through non-financial measures as discussed earlier. The reasons for this approach are the availability of data in public domain particular to data services provided by mobile operators, lack of studies in performance assessment using non-account-based measures and looking at the latest technology adoption by mobile operators.

The technical variables required for empirical investigation of performances in mobile data services are selected by applying the Maslow's hierarchy of needs for human growth framework. The basic idea of this framework is that people need to meet the most primitive and basic needs before satisfying their higher needs [45]. For instance, one who cannot have access to basic needs such as food and shelter, friendship and realizing personal potential are irrelevant. Applying this analogy to mobile data services, the technical parameters needed to deliver the facilities from foundational requirements to higher-level requirements are structured in Figure 9.

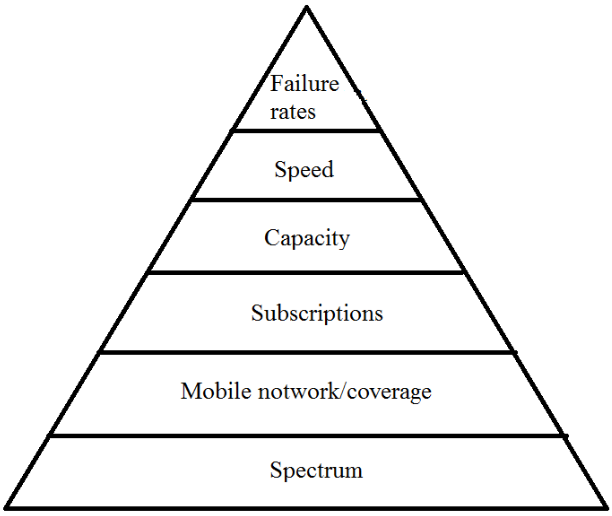


Figure (9) Mobile data services driven heirarchy of needs.

The basic requirement for any MNO to provide any service to their customers depends on its spectrum holdings. The roll-out of spectrum allocations is driven by regulators to accommodate the newest mobile communication technologies. At the same time, MNOs are increasing their spectrum holdings to deliver these technologies for market survival and various amenities provision. The advancement in technologies also bringing the challenges to deliver and use the newest mobile broadband data services. However, on the other end, it is also important to use the held spectrum by any MNO effectively and efficiently. These reasons make the spectrum is a fundamental parameter for provisioning data services.

At the next level, providing the mobile network from basic to advanced facilities (different network modes) across all geographical areas where MNOs are holding the spectrum or depending the customer demands. This also relates to coverage or availability of the mobile network. Besides, the availability of the network depends on the infrastructure built by the MNO. Instead of looking deep into the details about how the operator achieving the coverage area requirements, the availability percentage of a particular technology is important at a broader level. Once the operator builds their network it is important to attract the potential customers and scaling up their infrastructure for the data services requirements. Further, MNO should work on delivering the data services and achieving the customer demands with building additional infrastructure, coverage and efficient spectrum usage. Once the MNO is able to meet the customer appetite to the data needs, it concentrates on the next level of deliverables, which are related to the quality of the services. These deliverables are average downlink and uplink speeds and connection failure rates. In overall, all the factors proceeding from a low level to a higher level of the pyramid are relatable to the mobile data services delivery.

In Figure 9, all the levels are relevant for data delivery to the customers but the important factors that contribute to the service delivery are spectrum, subscriptions or connections, data capacity, and speed. The other two factors coverage and failure rates, in which coverage pivots on MNOs spectrum licenses and customer penetration in any given geographical location; whereas failure rates are pertaining to the reliable connection delivered to the customers. In addition, most of the MNOs providing above 90% coverage area. Further, it is assumed that all the MNOs delivering 99.999% ("five nines") connection availability. Thus, these two factors are not considered in the study.

Table (3) Summary of selected inputs and outputs.

Inputs	Outputs
Number of connections	Data volume
Spectrum	Average speed (only for the study in appendix A)

From the four main measures, MNO can deliver data capacity or data volume and average speed to their customers depends on the number of connections in its network and spectrum holdings. The fundamental Shannon principle also supports capacity is directly proportional to the available bandwidth. There are limitations in data availability for the average speed variable. Thus, total data volume delivered to all the connections with using the spectrum available with each operator is the case understudy for the thesis work. In this case, inputs are the number of connections and spectrum; output is data volume and can build 2 input and 1 output DEA model for MNO's productive efficiency measurement (shown in Table 3). This study is discussed in chapter 5.

The DMUs are discarded form the study for which average speed data is not available. Then the efficiency measurements are done which is discussed in appendix A. In this, total data volume provided with an average speed provided to all the connections with using the spectrum available by each operator. In this case, inputs are the number of connections and spectrum; outputs are data volume and average speed; can build 2 input and 2 output DEA model for performance study. The results from this case are not concerned with thesis main results.

4.3 Decision making units selection

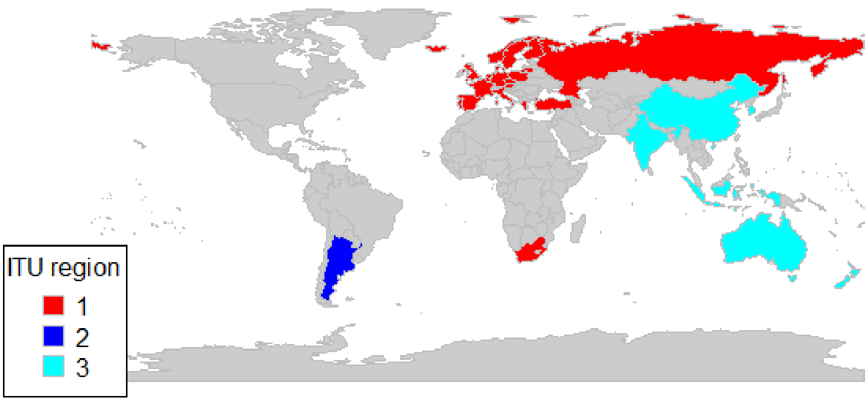


Figure (10) ITU region-wise selected countries for the study.

MNOs and countries are decision-making units (DMUs). Many MNOs are not disclosing data regarding total data volumes delivered within their network. This is a key challenge in data collection and restricts the number of MNOs considered, which in turn limits the number of countries for the study. Countries were selected for the study based majorly on the availability of input and output data for all MNOs of that country. All MNOs selected in a country should hold more than 90% of market share cumulatively, which would help us further to examine the differences at the country level. The data available for a limited number of operators in a particular country is not considered in the study, as it would not reflect the efficiency achievement differences at the country level. Besides, the countries with similar financial or social or regulative market conditions would benefit finding the dissimilarities effectively. In view of this, the data collection is prioritized as the countries belong to different economic groups or unions. The priority order to find the data was for all the countries belong to OECD countries, the European Union (EU) countries and G20 countries respectively. But due to lack of data availability, finally, selected nations for the study belongs to either of these three groups. Table 4 lists all the nations in the study and one can observe that 22 countries are OECD member nations and other 6 countries are part of the G20 group. Figure 10 highlights all the countries selected for the study depending on which ITU region these belong to with color separation. Ultimately, 94 MNOs from 28 different countries data used for the study.

Table (4) The countries selected for the study.

Region	Countries
ITU-1	Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Iceland, Italy, Lithuania, Netherlands, Norway, Poland, Portugal, Russia, South Africa, Spain, Sweden, Turkey, United Kingdom
ITU-2	Argentina
ITU-3	Australia, China, India, Indonesia, Korea, New Zealand

Further, the availability and collection of inputs data and outputs data are discussed in section 4.4.

4.4 Data availability and collection

Data collection is an exercise of arranging and accumulating the data in good order from various sources that have been noted, recorded and organized for a particular purpose. Consequently, the selection of a particular data collection method is regulated by the strategy, the type of variables and the source [16]. Accordingly, the data is segregated as primary data and secondary data. The primary data is acquired by experiments, surveys, and research to accomplish an objective of a specific study and which has not been available formerly. Conversely, secondary data is achieved through the use of data partly or fully or which has some relevance for the current study to be carried from the data set that was gathered for separate objectives [33]. Further, data is also divided by its sources viz. external sources and internal sources [14]. In this research, external secondary data have been used for the study. The data availability and its sources for the selected inputs and outputs parameters are discussed here.

The collection of quantitative data is a challenging task for the selected input and output parameters of MNOs under study. The challenge starts from finding the data from each operator's report and if any particular MNO has not listed all the data for the selected input and output parameters then it needs to look the data from other sources. Various sources are the backbone for the study due to nonavailability of the data from a single source and many MNOs were not disclosed their operational indexes in their reports. These sources range from operator annual reports to third-party industry analyses. Further, the challenges with data collection, all the terminology used by each source and all the sources used for data collection of each input and output measures are explained in following enumerated sections.

1. **Number of connections:**

   In general, the number of connections means total subscribers or SIMs served by the MNO. However, the term "number of connections" has been used in this study due to embedded SIMs adding to the traditional physical SIMs and number of IoT devices or M2M devices connected to the mobile network along with human subscribers. In addition, majority of MNOs are reporting their customer base with different terms such as number of prepaid customers, number of postpaid customers, business customers or corporate subscriptions, Smartphone customers, M2M connections, cellular IoT connections, active customers and mobile broadband customers. In view of this, the term number of connections keeps the uniformity for all the MNOs in the study. The number of connections equals to cumulative of various types of subscriptions served by the MNO.

   The prime sources for the number of connections are:

   - Operator reports
   - GSMA intelligence data

2. **Spectrum:**

   Various phrases have been using to illustrate a frequency band available for a particular service type, a specific technology or an individual firm. These phrases are allocation, identification, allotment, and assignment. In which, "allocation" is frequency band used for certain type of service by a national regulator, identification is to select which frequency bands compatible for different cellular technologies, allotment is frequency channel assigned for specific service under specific conditions and assignment is awarded frequency band to a user or firm by the national regulator [1]. Thus, the data search for spectrum in the sources heavily depended on these phrases. Consequently, the search for data followed as allocation to find mobile service bands, assignment to find bands granted for the 2G, 3G, 4G, and 5G services, assignment to which operators these frequency bands allocated. In consolidate, this approach has given data for the spectrum holdings with each MNO. Further, the mobile spectrum allocated up to 4G services is considered for the study and excluded mobile spectrum used for WiMAX and 5G services.

   The spectrum holding data is not available in most of the MNOs annual reports. In view of this, various other sources are looked for the relevant data needed. These sources are:

   - European Commissions Office (ECO) Frequency Information System (EFIS) for European operators

- Asia Pacific Telecommunity for Asia-Pacific operators
- Operator reports
- Spectrummonitorting.com
- other publicly available internet data

3. **Data volume:**

   The MNOs and third-party telecommunication reports have been using many terminologies to represent the data volume term. These terms are mobile data usage, mobile broadband data usage, 4G data usage, smartphone data usage and data usage by active users. However, the availability of data related to data volume or data usage is one of the biggest challenges for the study. Many MNOs are not disclosing this data in their key performance indicators or operational data or annual reports. Thus, many sources have been used for the collection of this data. These sources are:

   - Operator reports
   - Regulator reports
   - GSMA intelligence data
   - Tefficient analyses
   - Calculations (missing operator's data calculated by subtracting all other reported operator's data from the country's total data)

   Data availability of this variable is a key constraint for the study. Many major countries and major operators are not included in this study due to non-availability of this data either fully or partially. Even though few operators reported the data in particular major country but not included in the study which limits the study to evaluate the efficiency scores at the national level.

4. **Average speed:**

   Average speed is a parameter that represents the data download or upload speed by the customers in a given MNO's mobile network. Among these two, average download speed is a study of interest in this thesis. Availability of this data with operators is very limited. Most often MNOs depends on third-party measurement services such as Ookla's speedtest, Opensignal, and Netradar for their service quality performance metric. The approach towards the measurement of average speed by these services is different hence the results are. Therefore, data is collected from only one service i.e. Opensignal to maintain the similarity in the comparison. Additionally, a maximum number of MNOs data is available with Opensignal. However, the average speed is another constraint after the data volume which leads the study to have a major DEA analysis with 2 inputs and 1 output. Consequently, an additional study is included in appendix A with 2 inputs and 2 outputs DEA analysis with the available data.

4.5 Software availability

A multitude of statistical software packages are available to work on DEA analysis. They are broadly divided into open source and proprietary software packages. Open source software package gives greater flexibility to work on different aspects of analysis without incurring any cost, whereas proprietary packages are limited to the purchased features in the software package. There are studies in which the available DEA software packages and its features are emphasized extensively [13] [25]. Few important DEA software packages are listed in Table 5. In this thesis study, open source "rDEA" package in R programming language is used for the empirical analysis and verified the results with other open source packages listed in Table 5.

Table (5) Available software packages for DEA.

Software	Type	Reference
R	Open source	rDEA Benchmarking additiveDEA
Python	Open source	pyDEA
Other	Open source	Open Source DEA (http://opensourcedea.org/) MaxDEA(http://maxdea.com/MaxDEA.htm) DEAP (https://economics.uq.edu.au/cepa/software)
Other	Proprietary	SAITECH - DEA-Solver(http://opensourcedea.org/) Banxia - Frontier Analyst(https://banxia.com/frontier/) STATA - DEAS STATA - https://sourceforge.net/projects/deas/ Matlab - DEA Toolbox

5 Data analysis and empirical findings

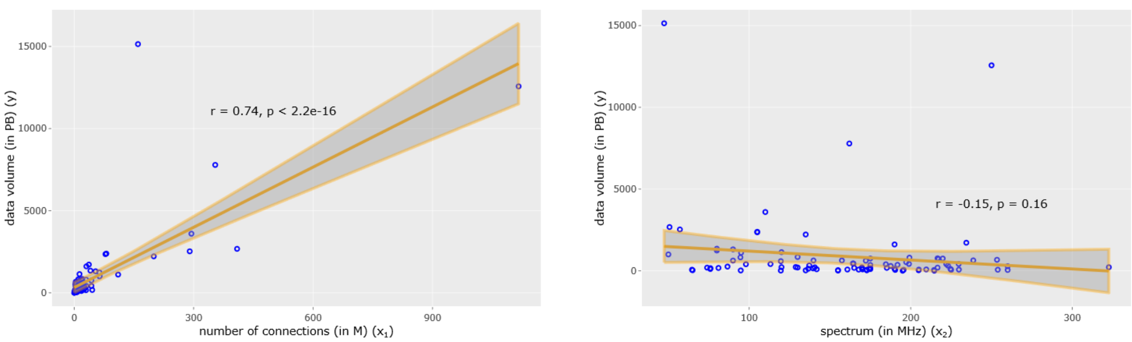
5.1 Data assessment

Descriptive statistics such as mean, median, standard deviation, minimum and maximum for the input variables and output variables are detailed in Table 6. The maximum values of connections and data usage are from a Chinese operator and the maximum spectrum value is from an Austrian operator, whereas the minimum number of connections and data usage are from Icelandic operators and minimum spectrum value from an Indian operator.

Table (6) descriptive statistics of data set.

Variables	Obs.	Mean	Median	Std. Dev.	Min	Max
Connections (in millions) (x_1)	94	45.11	10.26	132.86	0.149	1116
Spectrum (in MHz) (x_2)	94	159.95	168.8	57.91	47.38	322.6
Data Volume (in PB) (y)	94	1023	244	2181	4.24	15140

Figure 11 illustrates the correlations between the inputs and output variables. Unsurprisingly, connections and data volume are strongly positively correlated, whereas spectrum and data volume are very weakly negatively correlated. This suggests that spectrum scarcity might not be a major constraint in increasing data volumes delivered to the customers. 5G literature discusses increasing data volume density by 1000-fold as a key KPI of 5G. However, there is a possibility of increasing the data volumes of current generation mobile networks by using the available spectrum for most of the MNOs.



(a) connections vs data volume (b) spectrum vs data volume

Figure (11) Correlation between inputs and output variables

5.2 Efficiency analysis at the operator level

5.2.1 Productive efficiency of MNOs

Regarding operator efficiency, Figure 12 illustrates the efficiency of mobile data service delivery for the 94 operators ranked by efficiency scores (corresponding production frontier of this is shown in appendix B). Two operators, DNA (Finland) and Reliance Jio (India) are fully efficient. A further case study of these two operators and their dissimilar reasons for high efficiency is detailed in section 4.4. Also, notably, CK Hutchinson's Three brand is very efficient in most of their countries of operation (e.g. Austria, United Kingdom, Denmark and Sweden). Therefore, illustrating that even big telecom groups can be widely efficient. Figure 13 details efficiency of operators with the addition of a market share curve and ranked first by country of operation and then by descending order of market share. Interestingly, CK Hutchinson's Three brand also shows low market share in many of their markets. Thus, their efficiency may be driven by their status as upstart operators.

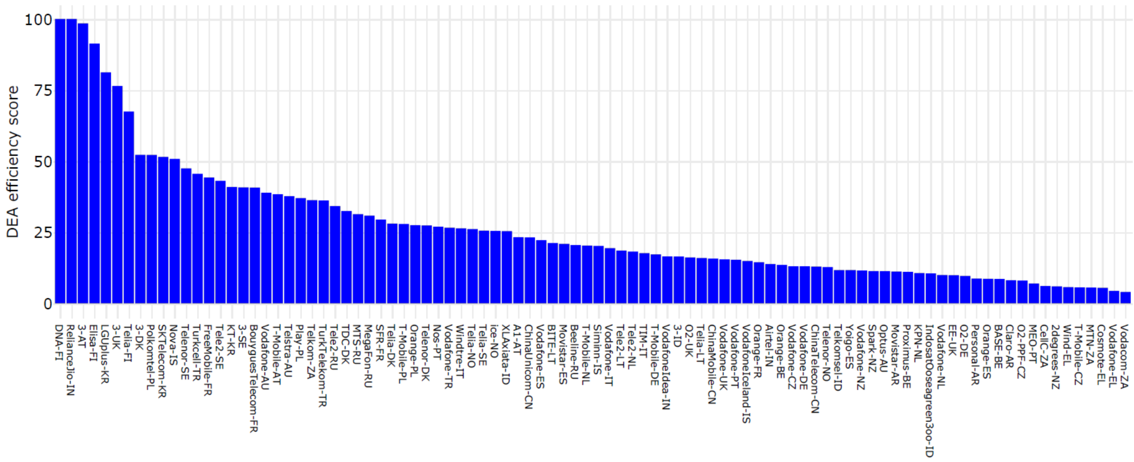


Figure (12) Productive efficiency scores of MNOs (in descending order).

Furthermore, in many countries, a single operator dominates in terms of efficiency the other operators in the same country; this phenomenon is discussed further in section 4.2.2. Though, in several cases, the operators of a single country are about equally efficient (e.g. Argentina, Belgium, China, Czech, Greece, Italy, Lithuania, New Zealand, and Russia). This scenario is hypothesized that this behavior may be due to strong regulatory policies.

5.2.2 Efficiency vs market share

It is observed that several cases where one MNO dominates in data service efficiency in comparison to the counterparts from the same country. In order to explain this behavior, market share has taken as an alternative performance measure (again see Figure 13). In 14 of 28 countries, the highly efficient MNO holds less market share.

Furthermore, in nine countries (including Austria, Finland, India, etc.) the highly efficient MNO is at least 10% more efficient than the second-best operator. This phenomenon is hypothesized with two reasons.

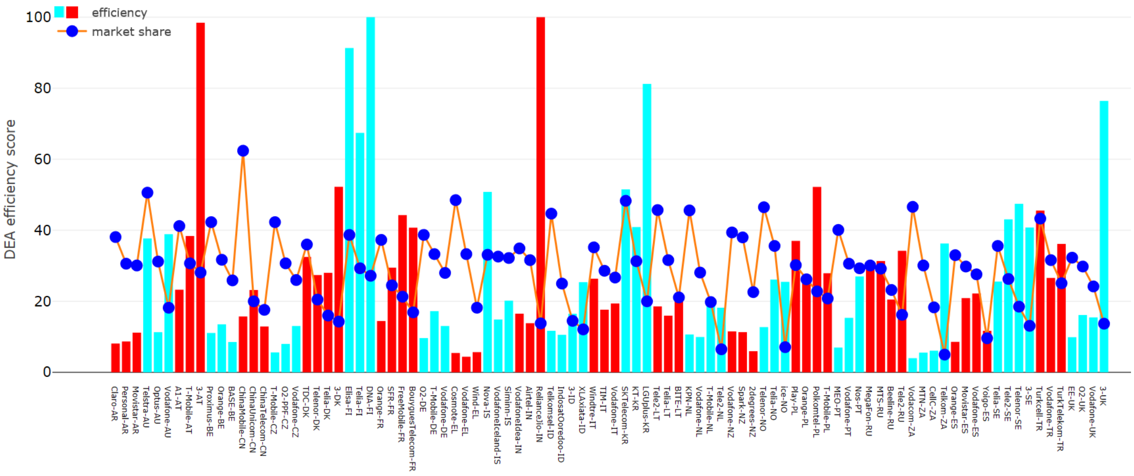


Figure (13) Efficiency scores and market shares of MNOs (ranked by country alphabetically and market shares descending order).

Firstly, all these operators are either the newest entrant or second newest entrant in their respective markets. In general, this gives a late-mover advantage as the new entrant can use the newest network technologies (3G and 4G) directly. All the newest mobile technologies are mobile-data driven and significantly more efficient in delivering data services. Thus, the newest entrants benefit. Conversely, established operators must satisfy both older generation mobile technology users and the latest mobile technology users. This scenario is predominant in developing countries such as India and Indonesia. Traditional operators in these countries might try to offer similar data services to users due to severe competition. However, their efficiency scores in data services is not as good as opponents because of their older technology, customer base, and lower penetration of mobile broadband.

Secondly, new entrant MNOs, even in mature telecom markets, look to quickly increase their market share to gain legitimacy. The common approaches towards gaining market share are pricing, data limit, and quality-based strategies. Aggressive strategies with higher data limits (or unlimited) and lower pricing thus attract high data usage users from traditional operators. Synergistically, the combination of high data limits and cheap prices attracts younger customers that are more price sensitive and use more data. This churn both significantly increases usage of the entrant and decreases the usage of the traditional operator.

5.3 Efficiency analysis at the country level

5.3.1 Productive efficiency of countries

Figure 14 shows efficiency analysis results at the country level. Finland, India and Korea are fully efficient in mobile data service delivery at the country level. Further investigation suggests that Finland and Korea are efficient for similar reasons, whereas India is efficient for significantly different reasons. Specifically, Finland and Korea are forerunners in the global telecommunications market. The success of countries is likely due to sustained effort towards the development of new mobile technologies.

Finland is a pioneer country in mobile communications with extensive coverage throughout the country. The major factors driving the highly efficiency include cooperative and fast adapting regulatory policies, high competition between MNOs, speed based rather than data volume based pricing, and high mobile over fixed broadband substitution.

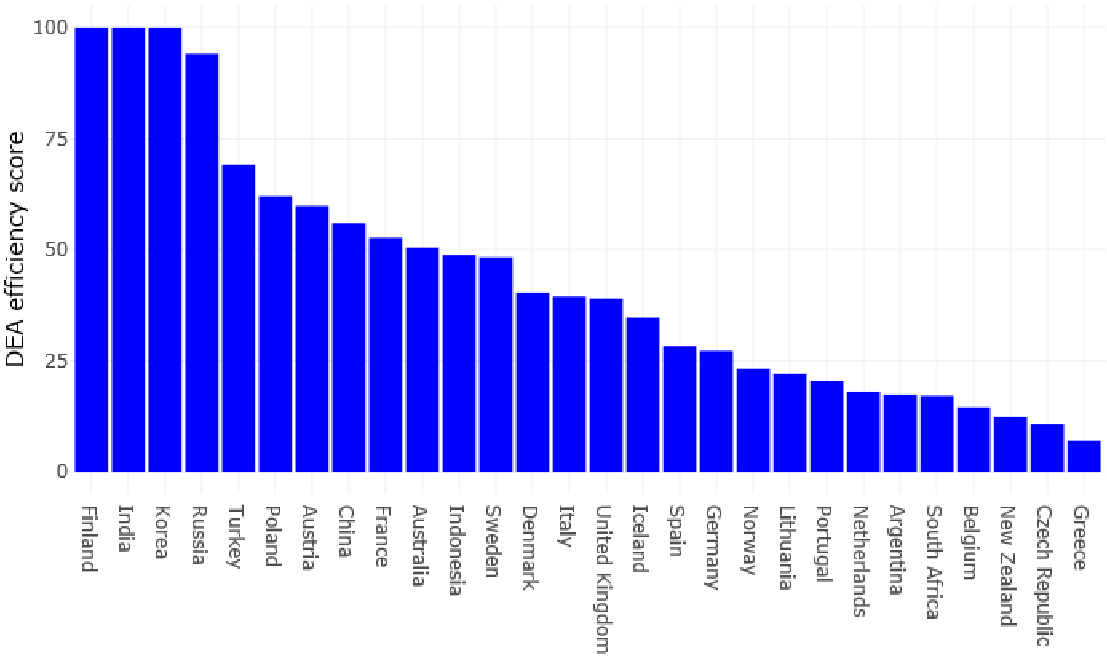


Figure (14) Efficiency scores of countries (in descending order).

At a broader level, the reasons behind the efficient performance of Korea are the sociocultural environments, citizen participation, the participation of major players (primarily handset manufacturers Samsung and LG; Operators KT, LG U plus and SK; research institute ETRI) in the development, and continuous support initiatives from the government towards mobile revolution and industrial support policies [38]. Particularly, the government initiated national infrastructure programs such as Cyber Korea (1999) to focus on providing resources for ICT systems and private investments and Korean Information Infrastructure (2015) to establish high-speed information infrastructure. Further, the government also supported both monetary and regulatory ways to promote broadband, ICT related R&D and standardization. Demographically, the Korean housing structure is densely populated, which made to provide broadband networks to 90% of the population without last mile delivery problem. At the same time, society acceptance also very high towards internet usage. Finally, extreme market competition between MNOs to grab new business opportunities through innovating alternative new products and services towards the rapid diffusion of mobile broadband services [23] [56].

On the other hand, India is efficient due to MNOs using very little spectrum relative to the traffic volumes, the lack of alternative (fixed) infrastructure for internet access, and the very high efficiency of the single operator Reliance Jio. The differences between India and Finland are further discussed in section 4.4.

Despite these countries' efficiency, the effectiveness of the data service should also be quantified by the quality of service. One such quality measure is the average connection speed. As per Open Signal 2017 data, the average 4G data speed was 40.44 Mbps in Korea, 26.62 Mbps in Finland and 6.07 Mbps in India. Therefore, though India is efficient, the quality of that data service is quite a bit lower than Korea and Finland. This lower service quality could be partly explained by the lack of spectrum of Indian operators, specifically 3-fold less than the Korean operators and 4-fold less than the Finnish operators.

5.3.2 Efficiency scores correlation with respect to various other measures

At the country level, many factors impact the mobile data services delivery and usage. These factors range from the technical to economical pertaining to each country. Thus, it is important to find the relation between such factors and how they are correlated with countries mobile data service efficiency scores. Due to the importance of such kind of analysis, the correlation analysis is adopted between DEA efficiency scores (Eff in percentage) and various other factors such as fixed-line broadband subscriptions per 100 people (FLBB in numbers), GDP at purchasing power parity per capita (GDP in USD), urban demographic percentage (Urban in percentage), price for 1GB of mobile data (Cost in USD) and average 4G speed (Speed in Mbps) (see Figure 15). In Figure 15, the values in the parenthesis represent the significance values and corresponding correlation values shown above to these values.

The correlation analysis brings out that the efficiency scores of mobile data services are negatively weakly correlated with four out of five other measures. On the other side, the efficiency score is statistically significant (unlikely to have null hypothesis) and a negative correlation with the price of mobile data. It is a straightforward situation that low data prices could attract users to use more data volumes. Additionally, the mobile data technology counterpart fixed-line broadband measure

FLBB is statistically significant and positively correlated with GDP (PPP), urban population and 4G network speed. Among all these, it is interesting to see the relationship between the fixed-line broadband network and the 4G network delivered speed. It explains that the majority of the countries (22 out of 28 countries) in the study are developed economies, thus the legacy of fixed-line broadband in developed economies could able to provide good backhaul network for mobile networks which in turn helps to maintain quality of service (QoS) guarantees. This scenario is the opposite in case of developing economies where they are jumping to mobile technology with a lack of fixed-line technology infrastructure for their data needs.

In overall, the fixed-line broadband measure is highly correlated with most of the parameters then the mobile data efficiency scores. Thus it would be fascinated to take the discussion of finding the mobile data usage dissimilarities in between countries by analyzing the traditional fixed-line broadband subscriptions data and mobile data efficiency scores which discussed in the following section.

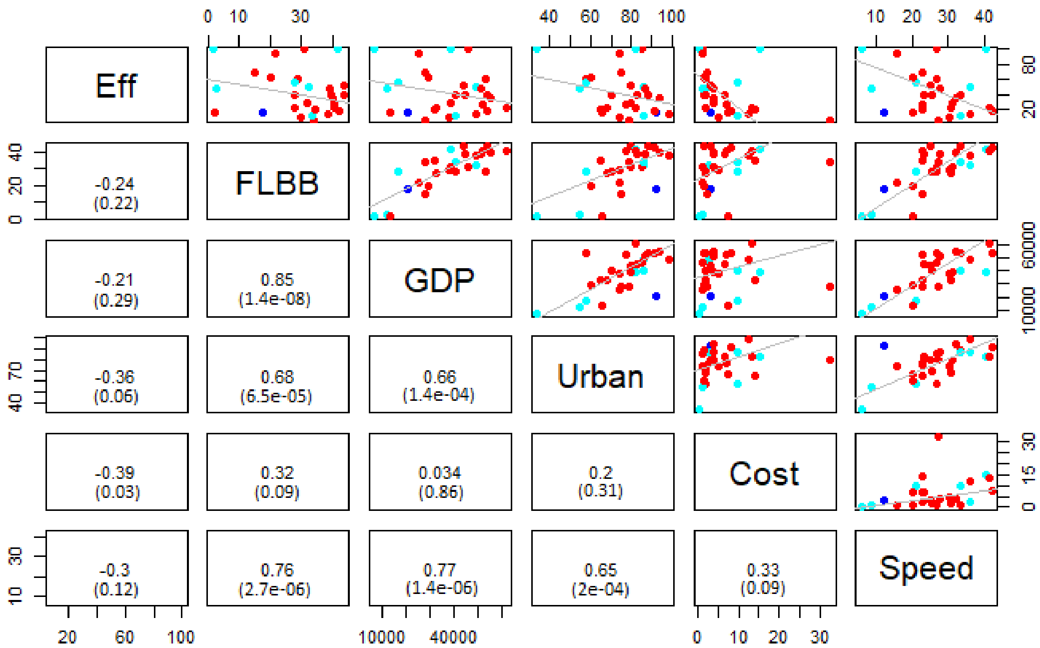


Figure (15) Correlation between DEA efficiency scores and various other measures of countries.

5.3.3 Efficiency vs fixed broadband subscriptions

This study also examined the country's efficiency scores in relation to traditional fixed-line broadband penetration. Figure 16 indicates that the efficiency score is weakly (non-significantly) negatively correlated with fixed-line broadband subscriptions per 100 people. Next, several different countries are compared and discussed with respect to its efficiency scores and fixed-line subscriptions.

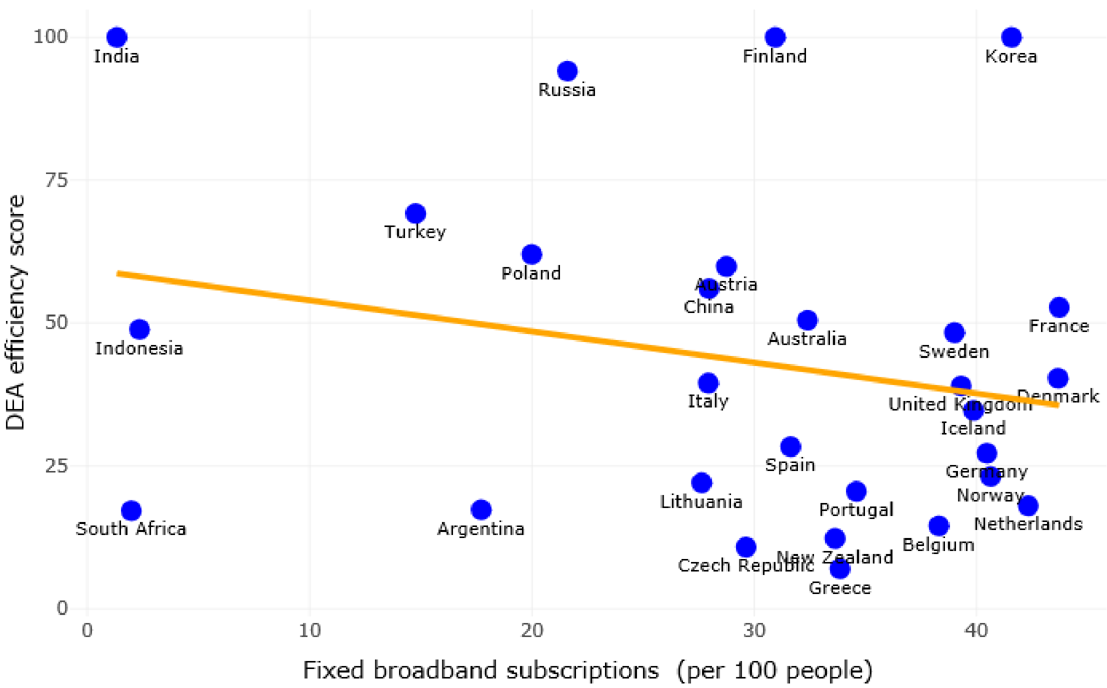


Figure (16) Comparison of country's mobile data efficiency scores with its fixed-line broadband subscriptions per 100 people.

For example, both Finland and Korea have high efficiency scores and high fixed-line subscriptions. Whilst Finnish and Korean customers are both large mobile data users, these two countries do have some significant differences. The edge is taken by mobile technology in Finland, whereas Korea uses more fixed line networks for data needs. Accordingly, mobile broadband penetration in Finland is 1.4 times higher than Korea and Korea holds more fixed line subscriptions than Finland. Additionally, the price per GB of mobile data is 13 fold higher in Korea than Finland.

Many countries could be considered either mobile efficiency dominant, fixed subscription dominant or roughly central in both. About 23 out of 28 countries could fall under this category. Developing nations such as Russia and India heavily depend on mobile data and perform well due to low spectrum usage. Although, China is also a developing nation it performed similarly to most of the developed nations. The remaining 20 countries are developed OECD countries with a high mean GDP per capita of USD 44K and a high mean urbanization rate of 79% in 2017. These countries enjoy higher fixed broadband subscriptions (per 100 people) with a mean of 34. Specifically, from Figure 16, about 72% of developed economies have low efficiency scores (below 50%) and high fixed line subscriptions (with an average of 35 subscriptions per 100 people). This pattern indicates that customers in developed nations might depend on fixed-line broadband as an alternative to mobile broadband for their data needs. This might be one of the causes for under performance of majority of OECD countries in mobile data efficiency.

Finally, roughly three countries have both low efficiency scores and low fixed-line subscriptions. These countries are developing nations with the GDP (PPP) per capita ranges from USD 12K to 20K. In these nations, the mobile broadband penetration and smartphone penetrations are above 90% and 76% respectively. These countries are demographically different with 92% urban population in Argentina and above 30% rural population in South Africa and Indonesia. Thus, Argentina could be able to provide more fixed line connections than the other two countries due to densely populated urban areas. Though, the three countries have good penetration of smartphones irrespective of demographic constraints, their mobile data usage per subscription is low. The customers are restricted to low data usage because of high cost (USD 7.19) per GB in South Africa. Contrastingly in Indonesia users have been increasing their data usage because of low cost (USD 1.21) per GB.

5.4 Case study on efficienies in Finland and India

The case study countries of Finland and India were chosen because of, first, leverage to find the data, second, strong evidence from empirical results. The former one is self-exposure and sources available to find in-depth information about both telecommunications markets. The latter part suggests that these countries are fully efficient at the country level. Additionally, at the operator level, the fully efficient operators of DNA and Reliance Jio operate in Finland and India respectively. Also, other operators in Finland have achieved relatively good efficiency scores, whereas no other operators in India achieved a good efficiency score. Thus, this suggests an interesting contrast.

More specifically, Finland's mean operator efficiency score is 86.25%, while India's mean operator efficiency score is 43.5%. Generally, Finland has strong technological advantages and effective policy implementations. While India has quite ineffective policy implementations. Furthermore, economically, Finland is a developed market and India is an emerging market. In the following the detailed differences between Finland and India are discussed with respect to regulatory policies, spectrum management, market situation, and economics.

1. **Regulatory policies**

   Finland was one of the first countries to start deregulation of telecommunications and has been implementing such policies effectively and consistently. Consequently, the telecommunications regulatory reforms are mostly pioneering and favor market openness and free competition. As part of the EU, Finland implements the EU legislation widely. The ministry of transport and telecommunications (LVM) is responsible for regulation drafting, policy-making, guiding and supervising the operations of its agencies. Finnish regulatory body, Finnish Communications Regulatory Authority (FICORA) (now as TRAFICOM) as an agency under LVM is responsible for regulatory framework implementations, radio frequency allocations, and market competitions. The Finnish telecommunications market is transparent and non-biased. Encouraging political decisions, along with technical developments, have also helped Finland to succeed in telecommunications. However, a few major setbacks in policy implementations of late include deregulation of anti-bundling [32] and market-based assignment of the 2600MHz band [57].

In India, the regulatory body operations and policy implementations have fallen well short of expectations. A major reason is the duplication of regulatory activities between regulatory bodies, including Telecom Regulatory Authority of India (TRAI) and other bodies in Department of Telecommunications (DoT) [30]. Further, this duplication limits accountability. Even when the TRAI does initiate recommendations, they must pass through many bureaucratic levels and the original recommendations might not be approved as it is or might causes an interruption in the process [58]. Additionally, political meddling in bureaucracy along with delays in merger & acquisition, spectrum scarcity, and poorly organized auctions also contribute to inhibiting the operator to provide seamless services across the nation [24]. These studies illustrating the infective regulation policies but the impact of these policies on mobile data efficiency pattern need a further study in India.

2. **Spectrum allocations and management**

   Regulatory policies pertaining to spectrum allocations is one of the fundamental and major differences between both countries. Sridhar et al. analyzed the differences between Indian and Finnish spectrum management policies extensively for mobile broadband services. According to their study, Finland regulator, FICORA has been allocating spectrum to the operators based on beauty contest method with a motive to develop new technologies and being a forerunner in technological evolution. On the other hand, TRAI has been adopting an auction method, which is a market-driven mechanism and with a prime objective to increase the revenue from the telecom sector [57]. Further, the spectrum allocation policies followed by India worked well to increase the competition and revenue generation for the government in the past. Nevertheless, eventually an overburden of high initial investments on the spectrum and low revenue generation deterred operators from investing in spectrum holdings and potentially delayed the deployment of new technologies.

   Finland is also a forerunner in spectrum refarming efforts compared to India. Spectrum refarming brings greater spectral efficiency by using the spectrum with newer more efficient mobile technologies. Spectrum reframing is a very slow process in India partly because 64.67% (only 11% in Finland) of subscribers still depend on 2G services [3], slow investments to replace older equipment and excessive spectrum fragmentation (in India spectrum is allocated differently based in 22 geographic circles rather than country wide).

3. **Market situation and competition**

   The telecommunications market situation is entirely different pre and post entry of Reliance Jio in India. There were more than 10 operators before the entry of Jio into the market which then converged to oligopoly situation after Jio's entry with currently four major operators (95% market share) in the market. Jio entered the market by solely adopting the latest LTE technology with a predatory pricing model. Jio offered services to satisfy the needs of both traditional and technologically savvy mobile users. For traditional users, Jio offered unlimited voice calls using VoLTE as most customers in India rely on voice services. However, existing feature phones did not have VoLTE support. Thus, Jio offered low priced handsets with VoLTE support as part of its service packages. Additionally, it also offered 1GB/day mobile service to attract younger savvy customers. All these approaches helped Reliance Jio gain 281 million subscribers within two years of operation [7]. Many established MNOs either merged, exited, or were acquired due to the fierce competition. The remaining MNOs were forced to offer similar packages as Jio or deploy entirely new business models. Customers benefitted from this market competition through mobile data services with higher capacities at cheaper prices. Overall, mobile broadband penetration and usage increased. However, the long-term profitability of Jio is uncertain and the operator (and in fact all major Indian operators) are currently loss-making.

   In contrast, Finland's mobile market is quite mature. However, the Finnish mobile market also confronted a similar situation previously. The situation in Finland was driven by Elisa's trailblazing mobile plans post-2010. Specifically, Elisa introduced unlimited mobile data plans with a flat pricing model, then other operators offered similar packages in the market due to the demand for high data volumes. Furthermore, Elisa launched plans based on speed tiers thus changing the axis of competition from data volume to data speed. This combination has driven huge traffic growth in Finnish mobile networks. Additionally, Finnish MNOs have been forerunners in upgrading existing technologies and deploying new tech. For example, high network automation (auto-optimization) has become a necessity due to the combination of huge traffic growth and slow revenue growth. Other MNO initiatives include testbeds for 5G technology, carrier aggregation to increase the data capacity in LTE, IoT services through NB-IoT, and smart city pilot projects.

4. **Economic differences**

   Economic differences are influenced the mobile data services between Finland and India. According to World Bank data, GDP per capita (PPP) of India was 6.5 times less than Finland for the year 2017. These economic differences are strongly related to mobile broadband penetration with a share of 30.39% in India and 162.86% at the end of 2017 [3]. However, the penetration is about five times less in India than Finland but the average price for 1GB of data is 0.26USD in India and 1.16USD in Finland [5]. The lower price of mobile data is also quite a significant determinant for the efficiency achievement of India.

6 Results and Future research

6.1 Results

The main objective of the thesis was finding the reasons behind dissimilarities in mobile data usage at the operator level and country level through performance analysis. This evaluation was realized by adopting CCR-DEA model and finds the performance through relative efficiency scores of 94 MNOs in 28 countries across the globe for the year 2017. Besides, this study used non-financial parameters to reflect the operator's performance with a number of connections and spectrum as input variables and data volume as output variables. At first, the CCR method employed on the data set to find the efficiency at the operator level. Then the data of each operator is aggregated in a particular country to achieve country-level data then applied CCR method to find the efficiency at country level.

The data analysis revealed a flat relation between an MNO's available spectrum and the data usage of their customers. In other words, only a few MNOs using their available spectrum efficiently while many others are simply holding large reserves of the inefficiently used spectrum. These reserves could be effectively used in the future to deliver more data with current-generation mobile technologies.

This study has quantified the differences in mobile data efficiencies at the operator level with the use of resources used for mobile data delivery. Two important patterns can be drawn from the results. First, a new entrant pushes to gain the market share and the customer base utilizing late-mover advantage by using new mobile technologies. This case is often found where only one operator shown high-efficiency score (e.g., Reliance Jio (India) and 3 (Austria)). Second, regulation policies that encourage innovation and adoption of advanced technologies. This case is where all the three operators in a particular country achieved relatively good efficiency scores (e.g., operators in Finland and Korea).

Further, at the country level, developed nations (Finland and Korea) and a developing nation (India) are displayed as efficient countries. The developed nation's motive is an urge to innovate and implement the newest technologies to boost their ICT systems associated economy, whereas developing nation highly dependent on mobile internet data due to the lack of fixed-line networks (e.g. India). Further, the efficiency of mobile data service compared with traditional fixed-line subscriptions. This disclosed that users are using fixed-line broadband as an alternative for data usage in developed nations with low-efficiency scores.

The case study between India and Finland brought different aspects of operations and reasons for the efficiency of MNOs in mobile data. These reasons range from economic situations, market strategies, user penetration, regulation policies, government initiatives, technology adoption, spectrum usage and alternative infrastructure for data usage.

6.2 Assessment of results

The DEA method is strongly associated with production theory principles. It will allow multiple inputs and multiple outputs irrespective of their dimensions. Given this advantage, the DEA method also useful in operations management for benchmarking the firms. Thus, this method is best fit to find the differences in mobile data service operations provided by the MNOs in different countries through efficiency scores, which is the main objective of this thesis study.

As mobile technology advanced from 2G GSM to 4G LTE technologies the network speed and capacity has been enhanced rapidly. Though first mobile broadband was supported by the 3G standard, the 4G technology authenticates true mobile broadband. Consequently, the latest mobile technologies are designed to deliver higher data capacities. The operators who entered newly into the market are benefitting from it. The empirical efficiency scores from the DEA method also indicated the same. The latest entrant MNO in a given country outperforms the pioneers by using fewer resources to generate higher data capacities. Additionally, innovative late movers are desired to gain market share using mobile data services. This has been created significant differences in mobile data usage at the operator level.

Most developed economies have well-deployed with legacy fixed-line broadband infrastructure. Thus, users in developed economies have an alternative to mobile data services to access broadband. This behavior is illuminated with the DEA efficiency scores at country level. Most of the developed economies shown lesser efficiency scores which have higher fixed-line broadband subscriptions. Further, the extensive literature study for the differences at country level elucidated the prime reasons for mobile data usage differences at the country level. These reasons are socioeconomic differences, affordability or price of the services and country or regulatory initiatives.

6.3 Exploitation of results

The thesis results are primarily helpful to the regulatory bodies to understand the performance of mobile operators in mobile data service operations. A regulatory body can evaluate the resources usage, importantly spectrum, used by the MNOs. Additionally, it can understand the business operations and strategies followed by the new entrants and incumbent firms in the industry. And also, the regulatory body can take insights from high performing countries where regulatory policies are effective. Thus, it can amend the existing policy or forming the new policy towards the effective use of resources or streamlining the services.

The thesis process and results are also applicable to MNO's operations research team or its consultants. This approach allows them to benchmark the telecom operations with their contestants and overhead spending on the resources. Besides, this helps to study the business process of competitors and combining these processes with their strengths to come up with better services in the market.

6.4 Future research

This thesis study recommends a few future research directions. First, the DEA method enables to include more variables for the study. However, one should take care of variables that are using for the study. This study unfolds that "average speed" can be added as the fourth variable or second output in the study without any problem, which also facilitates the study to look from the service quality aspect aswell. Additionally, the use of advanced DEA models will help to correct the DEA efficiency scores of MNOs where bias and heterogeneity observed in the data set. It also estimates a confidence interval for the noise exists in the data.

Second, the usage of the Malmquist productivity index[8] will be helpful to portray the mobile data delivery efficiency scores of the MNOs change over the years. Additionally, this allows observing the shift in the frontier technology by which one can fragment productivity as an innovation or technological change and productive technical efficiency. Further, this composition might also expedite to see the impact of regulatory policy changes on MNOs operations or conversely a single MNO's bold move in the market could lead to changes in the policy in the timeline considered for the study. However, the relevant data gathering process will be a significant challenge for this study.

Third, average speed as one of the QoS parameters has shown a notable correlation between available spectrum and fixed-line connections at the country-level analysis. Beside, MNO with low spectrum in the nation with higher fixed-line connections could able to deliver speeds on par with its counterparts. Thus, research questions can be raised from this is Why the MNOs in better fixed-line infrastructure nations could able to deliver better mobile data speeds? And subsequently, what kind of strategies followed by the MNOs with the low spectrum to compete with other MNOs in these nations?

[8] Malmquist index was introduced by Malmquist in 1953 and many authors further have been developed the extensions to suit non-parametric framework. It estimates the DMU's efficiency change over time. [59]

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A Two inputs and two outputs case

As explained in section 4.2, the variable "average speed" is not considered in the main study due to nonavailability of data. Thus, this appendix section illustrates the results and discussion of the empirical study by including the average speed as a second output variable. This study unfolds the results with the available data.

A.1 Data

The 94 observations (or MNOs/DMUs) in the main thesis study (with two inputs and one output) reduced to 55 observations (or MNOs/DMUs) in the present study due to nonavailability of data for average speed. Here, these 55 MNOs belongs to 16 countries (whereas 28 countries in the main study). The data collection and gathering process is explained in section 4.4 for all four variables. Table A1 details the statistics of all the variables (two inputs and two outputs) for all 55 MNOs. The maximum number of connections and data volume are from Indian operators and the minimum number of connections and data volume are from a Norwegian operator. Additionally, the minimum spectrum value from an Indian operator and maximum spectrum value from British operators. Further, the minimum average speed delivered by the Indonesian operator and the maximum average speed delivered by the Norwegian operator.

Table (A1) descriptive statistics of data (for 2 inputs and 2 outputs case).

Variables	Obs.	Mean	Std. Dev.	Median	Min	Max
Connections (in millions)(x_1)	55	34.36	72.74	9.95	0.456	409.03
Spectrum (in MHz) (x_2)	55	150.2	57.16	164.6	47.38	260
Data Volume (in PB) (y_1)	55	697.7	2064.8	205.6	21.9	15140
Avg. speed (in Mbps) (y_2)	55	20.98	11.48	22	2.04	47.08

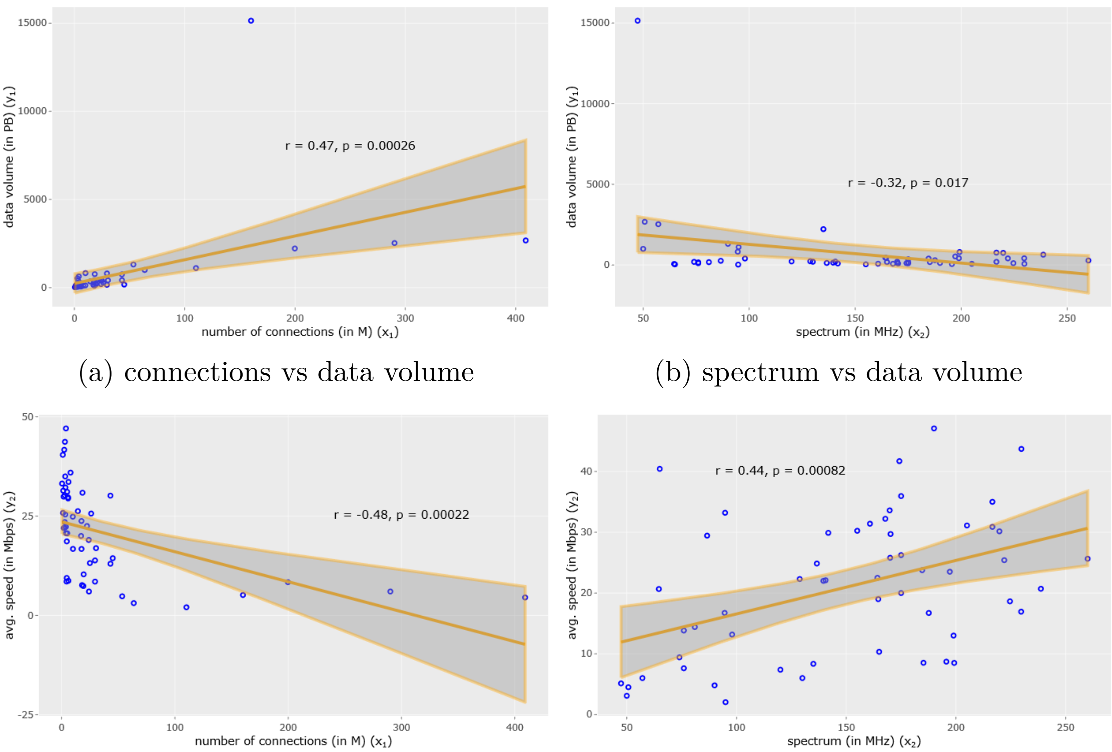
The 16 countries under this study are listed in Table A2 according to which ITU region each country belongs to.

Table (A2) The countries selected for the study (for 2 inputs and 2 outputs case).

Region	Countries
ITU-1	Belgium, Denmark, Finland, Germany, Italy, Netherlands, Norway, Portugal, South Africa, Spain, Sweden, United Kingdom
ITU-2	Argentina
ITU-3	Australia, India, Indonesia

A.2 Bivariate analysis

Figure A1 depicts the correlation between input variables and output variables using bivariate analysis. This bivariate analysis brings out two characteristics from the data. Firstly, the first input variable "number of connections" (x_1) is positively correlated with first output variable "data volume" (y_1) and negatively correlated with second output variable "average speed" (y_2). This relation makes apparent that the congestion problem is evident to deliver the mobile data with good data speeds when the number of connections added into the mobile network. However, this phenomena depends hugely on spectrum availability with the MNO and its effective usage. Secondly, the second input variable "spectrum" (x_2) is negatively weakly correlated with data volume (y_1) and positively correlated with average speed (y_2). The observation, in this case, is that MNOs can provide future data needs with the present mobile technologies and currently available spectrum (similar to the observation made in section 4.2). Further, the negative correlation between spectrum and average speed illustrates that MNOs with the higher spectrum could able to deliver better data speeds than their counterparts.



(a) connections vs data volume

(b) spectrum vs data volume

(c) connections vs avg. speed

(d) spectrum vs avg. speed

Figure (A1) Correlation between inputs and outputs variables

A.3 Productive efficiency

The CCR-DEA method applied to the collected data set for 55 DMUs (MNOs). The empirical results of the analysis are shown in Figure A2 in the descending order of efficiency scores achieved by each MNO. The results illustrate that four MNOs are fully efficient. These four MNOs are DNA (Finland), Ice (Norway), Reliance Jio (India) and Tele2 (Netherlands). In which, DNA and Reliance Jio are fully efficient in the main study. Ice and Tele2 are first-lowest and second-lowest MNOs respectively with the customer base and data volume value in the data set. These two MNOs achieved full efficiency score due to low usage of spectrum and provided the data with good average speed.

Further, the results show that all Finnish operators are attained relatively good efficiency scores and CK Hutchinson's Three brand is efficient in most of their countries of operation. These results are similar to the results in the main study. However, the MNOs efficiency scores need to be compared with its market shares in their country of operation to find more reasons for the dissimilarities in mobile data services. This discussion is explained in the following section.

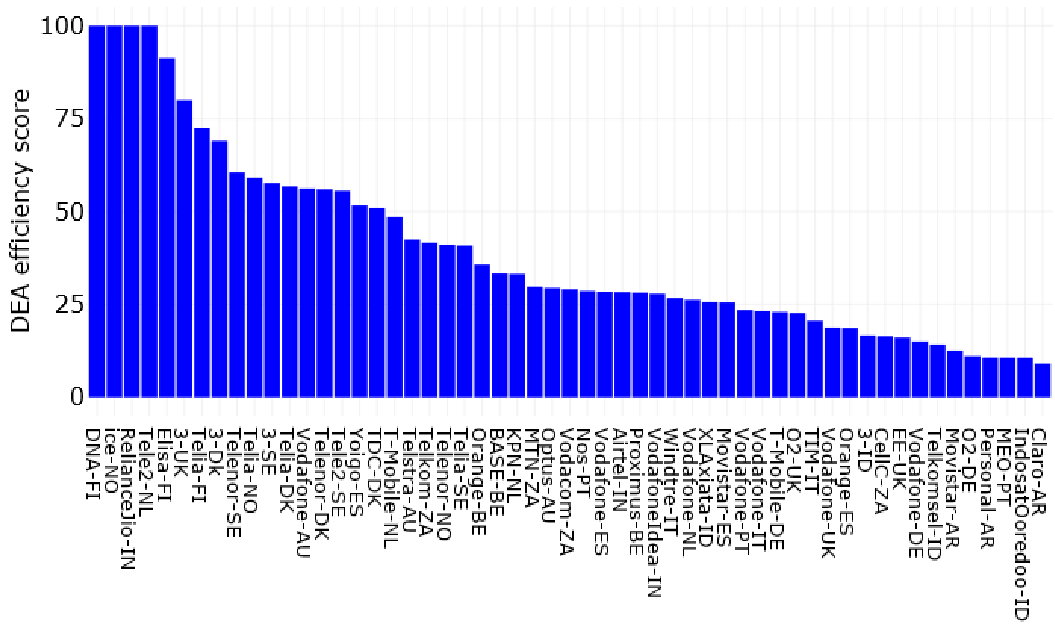


Figure (A2) Productive efficiency scores of MNOs (two input and two output).

A.4 Efficiency vs market share

Figure A3 represents the efficiency score of operators with its market share curve and grouped by country of operation and then descending order of market share. In this study, it is observed that 12 of 16 countries, the MNO with data efficiency score has the lowest market share in its country of operation. Besides, the highly efficient MNO is at least 9% more efficient than the second-best efficient operator in ten countries (including Australia, Finland, India, Netherlands, Norway, etc.). This phenomenon is similar to the results explained in sub-section 5.2.2. Thus, the hypothesized two reasons in sub-section 5.2.2 are still valid in the present case also.

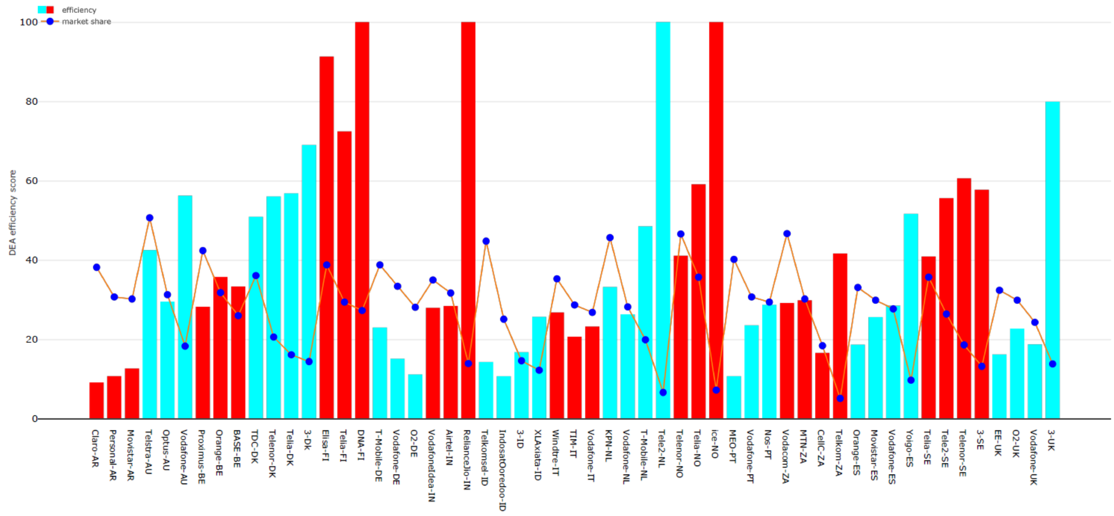


Figure (A3) Efficiency scores and market shares of MNOs (two input and two output).

B Production frontier

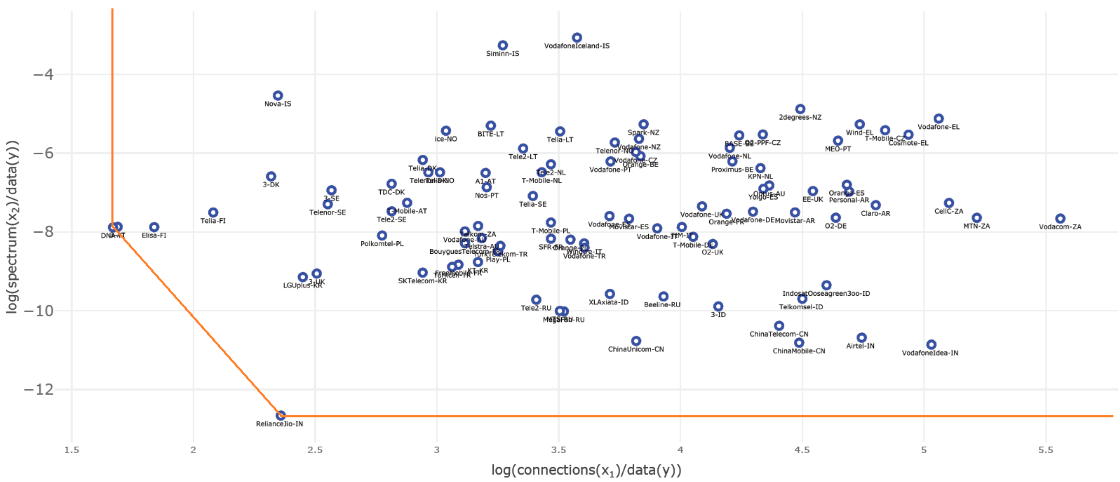


Figure (B1) DEA production frontier (two inputs and one output).