Evaluating Customer Service Representative Staff Allocation and Meeting Customer Satisfaction Benchmarks: DEA Bank Branch Analysis

M.A.Sc Thesis

by

Elizabeth Jeeyoung Min

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Supervisor

Dr. Joseph C. Paradi, Ph.D., P.Eng., FCAE

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Abstract

This research employs a non-parametric, fractional, linear programming method, Data Envelopment Analysis to examine the Customer Service Representative resource allocation efficiency of a major Canadian bank’s model. Two DEA models are proposed, (1) to evaluate the Bank’s national branch network in the context of employment only, by minimizing Full Time Equivalent (FTE) while maximizing over-the-counter (OTC) transaction volume; and (2) to evaluate the efficacy of the Bank’s own model in meeting the desired customer satisfaction benchmarks by maximizing fraction of transactions completed under management’s target time. Non-controllable constant-returns-to-scale and variable-returns-to-scale model results are presented and further broken down into branch size segments and geographical regions for analysis. A comparison is conducted between the DEA model results and the Bank’s performance ratios and benchmarks, validating the use of the proposed DEA models for resource allocation efficiency analysis in the banking industry.
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**EXECUTIVE SUMMARY**

The main objective of this study is to evaluate one of Canada’s ‘Big Five’ bank’s Customer Service Representative (CSR) allocation model for their branches by (1) evaluating the efficiency of their national branch network in the context of employment only and (2) evaluating the efficacy of branch operations meeting the desired service time benchmarks. The study employed a non-parametric, fractional, linear programming method, Data Envelopment Analysis (DEA) and particularly, the non-controllable variables included in Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) models.

This study provides an overview of the Bank under study. It presents detailed information regarding the Bank’s branch network characteristics as well as the Bank’s Current staff allocating Model (BCM) and management’s decision making process. Moreover, the Bank’s performance measuring ratios and desired benchmark ratios are presented. To promote prompt service with reduced wait time in line, the Bank employs a target for transactions to be completed under a set number of minutes as a metric represented by a ratio to measure customer satisfaction. One of the key contributions of this research is providing insight into the Bank’s staffing model’s capability to meet the benchmark and also, to develop a valid performance measuring tool for management use.

Two DEA models are proposed to measure the efficiency of the BCM in assigning staff to the branches. The first DEA model evaluated the Bank’s national branch network consisting of 1166 branches after problematic branches were removed (data problems and outliers). The model is composed of 3 inputs, 2 outputs and 4 non-controllable inputs, based on the number of Full Time Equivalent (FTE) staff used to produce different types of over-the-counter transactions (volume). Non-controllable inputs include branch size, number of teams present, desired service time, and desired wait time, which help to define peer groups by providing branch characteristics and key model levers set by management. Both CRS and VRS results are presented and are further broken down into branch size groups and geographical regions for analysis. Average CRS and VRS DEA efficiency scores for all branches were 73%, and
with scale efficiency ranging from 0.98 to 1.0, the study was able to conclude that the Bank under study is operating at constant returns to scale.

CRS DEA results revealed that about 15% of the branches are efficient and measured a high average efficiency score of 73% for the Bank’s branch network. This result suggests that the BCM is, in fact, effective in allocating CSR resources across their national branch network but there are still potential for improvements as DEA was able to identify inefficient branches with efficiency scores ranging from 18% to the fully efficient, 100%.

The performance ratios used by the Bank were found to be not quite adequate to measure branch efficiency as they both showed a positive correlation to the branch size. Thus, when the performance ratio scores were compared to the DEA model efficiency scores, the result was inconclusive as it suggested no significant correlation.

The second DEA model evaluated 20 branches from the pool of their national branch network for which transaction-by-transaction timing data was available. This model is composed of 2 inputs, 1 output and 1 non-controllable input, based on the number of FTE staff used to produce transactions under 5 or 10 minutes depending on management’s desired benchmark set for each branch. A two part analysis was conducted to evaluate each branch’s efficiency as well as branch efficiency on an hourly average basis. Average CRS DEA efficiency scores revealed to be 78% and 65%, respectively. From these results, it was concluded that the BCM is effective in providing branch level staffing recommendations in allocating CSR staff across the national branch network; however, it still needs improvement in providing guidance on hourly staffing solutions.

DEA results were then compared to the Bank’s benchmark ratios. Correlation analysis revealed strong positive correlation between the proposed DEA model efficiency score and the Bank’s benchmark ratio with correlation coefficient of 0.70. This validates both the Bank’s BCM model and the proposed DEA model. The results suggest that DEA is, in fact, a suitable tool to evaluate the Bank’s staff allocation model’s efficacy with respect to the Bank’s desired benchmarks.
CHAPTER 1:

INTRODUCTION AND PROBLEM STATEMENT

Canadian banks have a major influence not only on the country’s economic development, but also on the entire society, owing to the increasing number of products and services aimed at providing convenience and flexibility to clients’ finance options. The diverse client base, ranging from individuals, to businesses, large corporations, governments, and non-profit organizations, helps banks to grow and organize their assets. The banks handle approximately 70% of total domestic assets in Canada, in which the ‘Big Five’ domestic banks\(^1\) account for over 90% of the assets held by the banking industry, and operate through an extensive network that includes over 5,300 branches across Canada [CANA03].

Due to changes in client needs and in response to growing demand for new financial products, the products and services banks offer range from simple personal banking to business, corporate banking, mutual funds, loans, mortgages and many others. Banks use multiple channels to handle these transactions, including and not limited to online banking, telephone banking, ABM and—most conventionally—through the branch network that serves as the main contact with existing as well as potential clients. Despite the rapid rise in the use of technology in banking, it was found that, in Canada, 61% of bank customers still visited branches in person and on average made four trips per month [NFO03].

In all industries, businesses must continuously grow and evolve to remain competitive, and large Canadian banks are no exception. In order for banks to remain competitive, it is essential to improve on branch network performance, where the majority of the transactions are still conducted, despite a number of alternative channels. The Bank in the present study is a firm believer of providing customers with the attention needed by providing as much direct contact with the customer service representatives as customers wish to have. Although the banking industry is under pressure to develop and fund new access channels, optimizing

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\(^1\) The ‘Big Five’ Banks are: “BMO Financial Group”, “CIBC”, “RBC Financial Group”, “ScotiaBank” and “TD Bank Financial Group”.
branch operation is still one of the key elements in reducing costs and increasing customer satisfaction. One of the major potential areas of improving branch network performance is through better human resources management. Effective deployment of resources allows the branch to perform at its best, thus meeting customer demand with the minimum required resources.

The concept of resource optimization and evaluation is not new; however, the increasingly complex products and services the banks presently offer have made evaluation of the appropriate employee requirements for the branches rather difficult. In addition, client-driven activities are usually difficult to predict, making staffing requirements challenging. Banks traditionally evaluated their performance through different financial measurements; however such conventional methods are often inconclusive and do not reflect the complex banking industry well [GIOK08]. Banks traditionally used concepts, such as historical trends and ratios, to measure efficiency; however, these analyses were usually two-dimensional measurements, insufficient when the branch performance needs to be compared to that of others. Moreover, such analyses fail to capture the multi-dimensionality and complexity of different branch activities [ORAL90].

In this study, frontier analysis approach is suggested as it is one of the widely employed methodologies to evaluate resource optimization for complex business units, such as bank branches. This approach is more effective than traditional methods, since they evaluate the branches’ relative efficiency against similar units and identify best performing units to build a frontier for reference in lieu of just comparing to an average value. Data Envelopment analysis (DEA), the frontier methodology employed in this thesis, is a non-parametric multi-dimensional approach that is capable of identifying the best performer units as well as recognizing complex relationships among the input and output components present in today’s bank branch network. Among its most significant features is its ability to simultaneously handle multiple indicators of performance as inputs and outputs, and thus, provide an unbiased comparison of similar units without prior specifications of the unknown underlying relationships. DEA's non-parametric nature determines its own model of the best practice unit.
This thesis focused on developing a comprehensive methodology that evaluates the efficiency of the branch staffing allocation process for one of the ‘Big Five’ banks in Canada. Using a non-parametric linear programming method, this study attempted to evaluate the Bank’s Current staff allocating Model (BCM) in regards to individual branch efficiency as well as in comparison to the Bank’s desired benchmarks. The proposed DEA model identifies the best practices of efficient branches, and evaluates the branch network across Canada. Moreover, the results gained from the proposed efficiency score based on a DEA analysis and the Bank’s own internal metrics were compared to each other for validation.

There are not many academic studies available to date that bring perspective to translating efficiency in terms of customer satisfaction. Most studies in performance measurement just focus on evaluating the current system and propose a methodology to effectively address efficiency improvements rather than comparing them to a benchmark that is desired by the management. The main objective of this research is to create a practical tool that has the ability to first identify, and thereafter evaluate unique opportunities and situations to potentially improve the staff allocation model, and providing a comparison to the Bank’s own metrics to assess how well their model is performing against their benchmarks.

Identified best-practice technologies and policies can be implemented, while DEA can also be used to determine which branches are most in need of restructuring, management replacement or closure. Proposed DEA models have been integrated with the existing planning tools utilized in the bank to establish policy guidelines in the planning, implementation and execution stages of the best branch identification for the analysis.

This study was carried out by collaborating with one of the major Canadian banks, using the data from their branch staff allocation model. The data collection and experimental components have been supported and carried out in collaboration with the Manager of Performance and Capacity Management. Throughout the research period, management has been actively involved, provided specific data, internal documents on branch operations and timely feedback.
1.1 Objectives

The objective of this study is to evaluate the Bank’s Current staff allocation Model (BCM) by measuring the performance efficiency of the Bank’s branch network. Employing a non-parametric linear programming method, Data Envelopment Analysis, this study attempted to identify efficient branches against the Bank’s benchmarks and potential areas of improvement in the model. There are two main parts to this study, (1) evaluating the BCM’s performance to identify best performing branches and overall effectiveness of the current model’s resource allocation across their national branch network, and (2) evaluating the BCM’s accuracy in meeting desired benchmarks set by the Bank in regards to satisfying customer demand.

By evaluating the model’s efficiency according to the desired benchmarks, management can (1) discover areas of improvements in the model, leading to (2) identifying guidance on how to determine the best staff mix in order to optimize resource allocation. The segregated regional and branch size analysis result (3) identify regional and branch size characteristics that needs to be employed to calibrate the model to fit different region and branch size allocations.

1.2 Method of Approach

The following chapters present the design and implementation of the research methodology, from its theoretical conception to its application.

- **Chapter 2 – Literature Review**, presents a detailed review of the relevant literature focusing on branch performance assessment, including parametric and non-parametric approaches.

- **Chapter 3 – Overview of the Bank’s Current Model (BCM) and Data**, describes the BCM employed by the management to staff CSR team across its branch network and an overview of statistical analysis on the data set.
• **Chapter 4 – Data Envelopment Analysis**, presents the research methodology, describing the theoretical background for Data Envelopment Analysis (DEA). It includes applicable DEA models: theory, terminology and mathematical formulations, as well as their applications.

• **Chapter 5 – DEA Model #1 Formulation and Results: Evaluating BCM’s Performance**, proposes the DEA model for BCM efficiency measurement and also presents the DEA results and analysis.

• **Chapter 6 – DEA Model #2 Formulation and Results: Evaluating BCM’s Accuracy**, proposes the DEA model for evaluating the accuracy of the BCM and also presents comparison between the DEA’s result and the Bank’s internal metrics.

• **Chapter 7 – Conclusions and Future Work**, concludes the thesis with the summary of work done, as well as the theoretical and empirical contributions of this research. The chapter also provides recommendations for future research.
CHAPTER 2:

LITERATURE REVIEW

This chapter presents an overview of past and present literature on evaluating performance of financial institutions at the corporate and branch levels. Ratio analysis marked the start of performance measurement in the banking industry and it is still the most commonly used method across different levels of management and decision-making processes in banks. While traditional methods such as ratio analysis are still valid and useful, complexity in the banking industry demanded a more sophisticated approach. In response, frontier methodology is the emerging performance measurement approach, allowing more complex use of information to provide insights into performance efficiency in the banking industry. Frontier methodologies are categorized into two main areas, parametric and non-parametric methods. This study uses Data Envelopment Analysis (DEA), one of the non-parametric techniques introduced in this chapter. Data envelopment analysis is reviewed in detail in Chapter 3.

2.1 Ratio Analysis: The Traditional Approach

Ratio analysis is the standard and historic method used by management to measure bank performance [GIOK08]. Ratio analysis compares two parameters to understand their relationship, offering insights into different aspects of bank operations, such as profitability, liquidity, asset quality, risk management strategies, and more. Traditional accounting ratios such as return on assets (ROA) and return on equity (ROE) have long been used to measure bank performance. Ratio analysis is still the major performance measurement tool in many industry settings, because it is simple to use and easy to compute and makes it possible to quantify the change in relationship over time [GIOK08].

Although ratio analysis does offer useful insights into bank performance, it is often incomplete and cannot represent the bank’s complex operation with its one-dimensional nature. Only one aspect at a time can be compared and no single aspect of an organization
can fully characterize the operation of a business [FED03]. Studies have attempted to combine ratios to form a more representative measure of bank performance; however such a task has proven to be very complicated and can provide contradictory results depending on different combinations [PARA04A]. Combining ratios is challenging since it is difficult to determine suitable weights for each efficiency component (ratio) a priori, to establish a representative combination [PARA11]. Another problem with ratio analysis is that it is objectively difficult to determine how far above the average is inefficient or efficient [GIOK08].

2.2 Frontier Efficiency Approach

The shortcomings of the traditional approaches have led to the development of a more sophisticated approach in measuring operational performance. Production units are the units in question for efficiency evaluation and in this particular study, bank branches. Frontier analysis measures the relative efficiency of production units based on the distance from the empirically estimated ‘best-practice’ frontier. Frontier efficiency analyses allow management to objectively identify best practices in complex operational environments.

There are five main approaches proposed in the literature as methods to evaluate bank efficiency, namely, data envelopment analysis (DEA) as in Charnes and Cooper [CHAR78]; free disposal hull (FDH) as in Tulkens [TULK93]; stochastic frontier approach (SFA), also called econometric frontier approach (EFA), as in Berger and Humphrey [BERG97]; thick frontier approach (TFA) as in Berger and Humphrey [BERG91]; and distribution-free approach (DFA) as in Berger, Hancock, and Humphrey [BERG93]; plus a rich literature on all of these approaches and variations of them.

There are two categories within the frontier efficiency analysis, they are parametric and non-parametric linear programming approaches. Parametric approaches include SFA, TFA, and DFA, and nonparametric approaches include DEA and FDH. These approaches primarily differ in the assumptions on the data in terms of (a) how much restriction is imposed on the specification of the best-practice frontier, and (b) the distributional assumptions imposed on the random error and inefficiency [BERG97].
There are two efficiency measurements: technical efficiency, which focuses on the level of inputs relative to the level of outputs; and economic efficiency, where a business has to choose its input and/or output levels and a mix to optimize an economic goal, usually cost minimization or profit maximization. This study measures technical efficiency, and price data is not included in the branch-level analysis.

2.2.1 Parametric Methods

There are three main parametric methods: stochastic frontier analysis (SFA), distribution-free approach (DFA), and thick frontier analysis (TFA). An advantage of the parametric methods is that they allow for random error, thus reducing the chance of misidentifying error or contamination of data as inefficiencies. Therefore the challenge in estimating with the parametric method is accurately separating the random error from inefficiency.

However, the parametric methods also have a disadvantage relative to the nonparametric methods because of having to impose more structure on the shape of the frontier by specifying a functional form for it [BAUE98]. The parametric model’s major weakness is that there is a possibility of specifying the wrong functional form leading to inaccurate efficiency estimates [GREB99].

2.2.1.1 Stochastic Frontier Analysis (SFA)

SFA has been the most-used parametric method since its introduction in 1977 by both Aigner et al. [AIGN77] and Meeusen and Van Den Broeck, independently. SFA formulates a frontier for a single input to multiple outputs or single output to multiple inputs scenarios. The SFA models random error using a standard normal distribution with a mean of zero and models inefficiency using an asymmetric half-normal distribution [BERG93]. The different distributional patterns allow the error to be separated from the inefficiency.

However, the half-normal distribution of inefficiency is relatively inflexible and assumes that most units are clustered near full efficiency. Studies including that of Berger and Humphrey [BERG97] have shown that specifying a more general truncated normal distribution for inefficiency yields statistically significant, different results compared to the half-normal
distribution. However, such increased flexibility makes it difficult to separate inefficiency from random error and shows a limitation to this approach.

2.2.1.2 Distribution-Free Approach (DFA)
DFA also specifies a functional form for the frontier. However, DFA assumes that random error averages out to zero over time, while efficiency remains stable over time [BAUE98]. It allows inefficiencies to adopt any distribution shape provided they remain non-negative. The inefficiency of each unit is calculated as the difference between its average residual and the average residual of a unit on the efficient frontier.

2.2.1.3 Thick Frontier Approach (TFA)
TFA uses the same functional form for the frontier as SFA, but measures the overall efficiency rather than the efficiency of an individual unit and thus does not assume any distribution in random error or inefficiency [BAUE98]. Therefore, units in the lowest average-cost quartile are assumed to have above-average efficiency and form a thick frontier, hence the name. Such a property reduces the effect of extreme points in the data, however provides limited understanding of the individual unit’s efficiency.

2.2.2 Non-Parametric Methods
Non-parametric methods include data envelopment analysis (DEA) and free disposal hull (FDH). Non-parametric methods impose less structure on the frontier but do not allow for random error, allowing vulnerability to inaccurately classify units as inefficient while error is present.

2.2.2.1 Data Envelopment Analysis (DEA)
DEA is a non-parametric linear programming methodology that develops production frontiers and measures the relative efficiency of the units to these frontiers. The most efficient units are those for which no other unit, or linear combination of units, has as much or more of every output (given input) or as little or less of every input (given output)
The DEA frontier is formed as the piecewise linear combinations that connect the set of these best-practice observations, yielding a convex production possibilities set.

DEA differs from its parametric counterparts in that it requires no explicit assumption or knowledge about the relationship between inputs and outputs, and hence DEA does not require any specification of the functional form of the frontier. However, DEA does not account for random error, causing its frontier to be sensitive to the presence of outliers and statistical noise [BAUE90].

As a performance measurement tool, DEA offers a strong ability to model complex and multidimensional operations by being able to handle multiple inputs and multiple outputs simultaneously. Unlike parametric methods that optimize a single regression plane through all the data, DEA optimizes each unit individually. Furthermore, DEA does not require any consistent metrics for its inputs and outputs, allowing varying scales to be compared simultaneously.

### 2.2.2.2 Free Disposal Hull (FDH)

FDH is a variation of DEA where instead of the piecewise linear frontier normally constructed; FDH constructs a stepwise frontier that measures efficiency only against real units of observation [BERG97]. Since the FDH frontier is either identical to or interior to the DEA frontier, FDH will typically generate larger estimates of average efficiency than DEA [BERG97].

### 2.2.3 Frontier Efficiency Method Comparisons

There are many studies on bank performance and use of frontier efficiency approach to measure performance, however there is not much information available to compare different approaches as most studies have applied a single efficiency approach at a time. There are a few studies that have compared multiple approaches, including Ferrier and Lovell [FERR90], Bauer et al. [BAUE93], Hasan and Hunter [HASA96], Berger and Mester [BERG97], Eisenbeis et al. [EISE97], Resti [REST97], and Berger and Hannan [BERG98].
There is no simple way to determine which of these methods best evaluates bank performance. The choice of measurement method appears to strongly affect the calculated efficiency and results have shown differences in ranking and inefficient unit percentages depending on the method [BERG93]. However, depending on the problem at hand, different methods offer advantageous edge in representing the relationship.

DEA has shown promising results in bank performance analysis ever since its introduction and researchers have produced studies at exponential growth over the last 30 years [EMRO08]. DEA gives a comparative ratio of the weighted sum of outputs to the weighted sum of inputs for each unit under evaluation. The relative score expressed as a number between 0 and 1 provides an efficiency measurement compared to the parametric methods, such as Cobb-Douglas functions, which use statistical averages to construct a particular measure of inefficiency, which may or may not be applicable to that unit’s composition [LIU01]. Not only that, DEA’s ability to analyze multiple inputs and multiple outputs is a strong advantage in evaluating a complex operation such as a bank. DEA with its non-parametric properties, indicates an easier yet sophisticated approach to tackle an industry problem, and was judged to be particularly suitable for this study. With the possibility of this study being further developed into an industry tool, DEA was chosen to measure bank performance in the current work. A detailed description of DEA models and theory follows in Chapter 3.

2.3 DEA in Bank Performance Evaluation

DEA is by far the most commonly used operations research technique in assessing bank performance. DEA was first introduced in 1978 by Charnes et al. and has been continuously developed and explored in various applications not limited to the financial industry but including health care, environmental studies, and more. At this time, there are a total of 163 studies that use DEA to assess bank efficiency and productivity. However, only 65 of these provide branch-level analysis [PARA11]. Sherman and Gold were the first to publish a bank branch network study using DEA, with a small sample data of 14 branches of a U.S. bank [SHER85]. Compared to easily accessible bank level data that is available publicly, branch-
level data is scarce and involves the institution in the study, thus the number of branch-level efficiency studies are much smaller in the literature compared to bank-level efficiency studies. It is significant to note that this study evaluates one of the top five Canadian banks and performs branch-level analysis on all currently operating branches across Canada, more than 1200 branches. This section summarizes recent developments of DEA use in bank studies over different model types and in literatures.

2.3.1 Model Types by Objectives
DEA branch-level studies can be classified into three model categories: production, intermediation, and profitability [PARA04A] [GIOK08]. The production model attempts to evaluate bank operations by using inputs such as labour and physical capital to produce output transactions, such as loans and deposits. When costs are considered, the production model evolves into a profitability model examining the operation's profitability of each branch [PARA04A]. The intermediation model assumes that the bank is a financial intermediary that transfers funds between savers and investors.

The production model is the most popular approach in bank analysis; many studies such as Schaffnit et al. [SCHA97], Vassiloglou and Giokas [VASS90], and Parkan [PARK87] have focused on developing production efficiency analyses using inputs of labour and computers, and office space and number of transactions as outputs. This thesis is unique in that it employed a production model but attempted to optimize customer satisfaction by reducing the time it takes to complete a transaction.

2.3.2 Model Variations
2.3.2.1 Constant returns to scale vs. Variable returns to scale
DEA can be implemented by assuming either constant returns to scale (CRS) or variable returns to scale (VRS). DEA started with a CRS model as proposed by Charnes et al. [CHAR78] and this model has been used in studies such as Parkan [PARK87], who evaluated a small sample (35 branches) of a large Canadian bank for operational efficiency using a CRS model. In most recent studies, researchers have argued that CRS is only suitable
when all units under evaluation are operating at an optimal scale [FETH10]. Schaffnit et al. [SCHA97] developed a VRS production efficiency model to examine 291 branches of a major Canadian bank. Since that time other studies, including Cook et al. [COOK00] who examined over 1300 Canadian branches, have increasingly used DEA models with the VRS assumptions.

### 2.3.2.2 Input-Oriented vs. Output-Oriented

Technical efficiency can be estimated under either an input-oriented or output-oriented approach. An input-oriented approach measures for a unit under evaluation, the amount of input change to produce the same output and become efficient. In contrast, an output-oriented approach measures for a unit under evaluation, the amount of output change needed with the same input, to become efficient. By far, bank performance efficiency studies have shown a strong tendency to use the input-oriented approach. This is because managers assume that inputs such as labour and capital are more highly controllable compared to common outputs such as profit, loans, and transactions [FETH10].

### 2.3.2.3 Multistage DEA Analysis

The two-stage concept in DEA was first introduced by Schinnar et al. [SCHI90] to measure the performance of mental health care programs. The two-stage DEA method, where the second stage uses the outputs of the first stage as its inputs, was applied by Wang et al. [WANG97] to assess the impact of information technology on firm performance. Gradually, use of the two-stage DEA method has increased in bank studies to analyze operations, profitability, and marketability, such as in Chen [CHEN02], Luo [LUO03], and Ho and Zhu [HO04], among others. Paradi et al. [PARA11] emphasizes the need to adopt two-stage evaluation for bank branch efficiency analysis to simultaneously benchmark the performance of operating units along different dimensions (production, profitability, and intermediation), in order to satisfy different managers and executives for much practical industry application. Paradi et al. [PARA11] developed a modified Slacks Based Measure model to aggregate the obtained efficiency from stage one to generate a composite performance index for each unit.
CHAPTER 3:

DATA ENVELOPMENT ANALYSIS (DEA)

This chapter presents an overview of the applied operations research technique used in this study, known as Data Envelopment Analysis (DEA). It includes a brief overview of its historical background, as well as detailed fundamental mathematical formulations and theories commonly used in DEA efficiency studies.

DEA started from maximizing a simple ratio of a single output over single input. Farrell [FARR57] introduced the concept of including multiple inputs and outputs and measuring relative efficiency of units in terms of radial contractions or expansions from the inefficient units to the efficient frontier. In general, there are two main DEA models used and they are known as CRS and VRS. The CRS model was first developed in 1978 and was applied for public sector and non-profit efficiency study as well as profit-oriented companies where the value of the outputs were either known, or unavailable/incomplete [CHAR78]. The VRS model was introduced in 1984 [BANK84]. Extensions to CRS and VRS model include Slack-Based Model (SBM) as well as categorical, non-discretionary variables and multiplier constraints as further discussed in this chapter.

3.1 DEA Theory and Mathematical Formulation

DEA defines a convex piecewise linear frontier composed of the ‘best-practice’ units which all receive an efficiency score of 1, while the inefficient units are projected onto this efficient frontier to calculate their efficiency score, which is less than 1. For each inefficient unit, DEA provides a set of benchmarks of other similar but efficient units to compare, providing useful information for management to recognize best practices as well as guidance on how to improve inefficient units and benchmark targets for them [COOP07].
In order to produce meaningful efficiency scores, there are few criteria the data must meet before the DEA analysis is done. Since DEA can be a benchmarking tool evaluating inefficient DMUs by comparing them to other efficient units, it is required that a DMU is, in fact, comparable in that they are similar in nature and operate in similar environments. As discussed in Chapter 2, DEA does not account for random error and DEA’s frontier is very sensitive to any measurement error, thus data must be thoroughly cleansed and all irregularities must be removed before the analysis [BERG97]. Also, a sufficient number of DMUs is needed to perform DEA. The number of degrees of freedom increases with the number of DMUs and decreases with the number of inputs and outputs [COOP07]. As proposed by Cooper et al, a general rule for the minimum number of DMUs (n) is that it should exceed the greater of the product of the input (m) and output (s) variables or three times the sum of the number of input (m) and output (s) variables [COOP07]:

\[ n \geq \max\{m \times s, 3(m + s)\} \quad (3.1) \]

Lastly, appropriate inputs and outputs must be chosen to represent the unit’s production process as the model requires, including all the resources impacting the outputs and all useful outcomes for evaluation. Furthermore, such inputs and outputs must be controllable by the management to produce significant results that can be applied in the industry.

Generally, efficiency can be measured as the ratio of outputs/inputs. The higher this ratio is, the more efficient the unit is:

\[ Efficiency \ Score \ of \ DMU_0 = \frac{\text{Output}_{0}}{\text{Input}_{0}} = \frac{\sum u_r y_{rj}}{\sum v_i x_{ij}} \quad (3.2) \]

Where
- \( y_{rj} \): quantity of the \( r \text{th} \) \((r=1, \ldots, s)\) output for unit \( j \) \((j = 1, \ldots, n)\)
- \( u_r \): weight associated with the \( r \text{th} \) output variable
- \( x_{ij} \): quantity of the \( i \text{th} \) \((i =1, \ldots, m)\) output variable for unit \( j \)
- \( v_i \): weight associated with the \( i \text{th} \) input variable
3.2 Constant Returns-to-Scale (CRS) Model

The CRS model is the first formulated DEA model as introduced by Charnes, Cooper and Rhodes [CHAR78]. The CRS model is built on the assumption that constant returns-to-scale (CRS) operation applies, implying that any increase in inputs results in proportional increase in outputs, regardless of the scale of operation. The CRS model finds a set of weights for each DMU that makes the DMU look as favourable as possible [CHAR78]. The goal of the model is to maximize the efficiency score ($\theta$) where every DMU uses total $X_j = \{x_{ij}\}$ amount of inputs to produce $Y_j = \{y_{ij}\}$ of outputs. Each DMU’s efficiency score is calculated relative to the other DMU’s efficiency score and it would only be considered efficient, when its score equals to 1 and both slacks from the efficiency: $s^-$ and $s^+$, are zero; otherwise, the DMU could be inefficient and the efficiency score will vary between 0 and 1. A DMU can be weakly efficient with a score of 1 even if slacks do exist. There are two orientations to CRS models and they are input orientation and output orientation.

3.2.1 Input-Oriented CRS Model

Equation (3.3) below depicts the formulation of the input oriented CRS model where efficiency scores are of n units:

$$\text{Maximize} \quad \theta = \frac{u_1 y_{1o} + u_2 y_{2o} + \cdots + u_s y_{so}}{v_1 x_{1o} + v_2 x_{2o} + \cdots + v_m x_{mo}} \quad (3.3)$$

Subject to:

$$\frac{u_1 y_{1j} + \cdots + u_s y_{sj}}{v_1 x_{1j} + \cdots + v_m x_{mj}} \leq 1 \quad (j = 1, \ldots, n)$$

$$v_1, v_2, \ldots, v_m \geq 0;$$

$$u_1, u_2, \ldots, u_s \geq 0$$

Where:

- $x_{ij} =$ the amount of the $i^{th}$ input to unit $j$
- $v_i =$ the weight given to the $i^{th}$ input
- $y_{ij} =$ the amount of the $r^{th}$ output from unit $j$
- $u_r =$ the weight given to the $r^{th}$ output
The above fractional CRS model can be transformed into the following less computationally intensive linear formulations: the primal and dual forms.

**CRS Input-Oriented Primal (3.4)**

\[
\max_{u,v} \quad p_o = u_1 y_{1o} + \cdots + u_s y_{so}
\]

**Subject to:**

\[
\sum_{j=1}^{n} x_{ij} \lambda_j
\]

\[
\sum_{k=1}^{s} u_k y_{ro} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \quad j = 1, \ldots, n
\]

\[
v_1, v_2, \ldots, v_m \geq 0;
\]

\[
u_1, u_2, \ldots, u_s \geq 0
\]

**CRS Input-Oriented Dual (3.5)**

\[
\min \quad \theta
\]

**Subject to:**

\[
\theta x_{io} \geq 0
\]

\[
y_{ro} \leq \sum_{j=1}^{n} y_{rj} \lambda_j
\]

\[
\sum_{r=1}^{s} y_{rj} \lambda_j - y_{ro} \quad i = 1, \ldots, m
\]

\[
r = 1, \ldots, s
\]

\[
\lambda_j \geq 0 \quad j = 1, \ldots, n
\]

\[
s_i^- \geq 0 \quad i = 1, \ldots, m
\]

\[
s_r^+ \geq 0 \quad r = 1, \ldots, s
\]

The dual form uses a set of non-negative intensity variables, \( \lambda \), to represent the weight of each of the \( n \) DMUs. The initial optimization is performed once for each DMU to reduce all inputs equally proportionally, bringing these DMUs closer to the frontier. Thus, optimality is achieved by minimizing inputs by a factor of \( \theta \) and indicates that inefficient DMUs would only require \( \theta \) amount (in percentage) of the inputs to produce the same amount of output. CRS models are radial models, as their goal is to adjust inputs or outputs (in the case of output orientation) radially from the origin. However, further input decreases or output increases may still be possible after radial optimization has been achieved.

Input excesses, \( s^- \), and output shortfalls, \( s^+ \), are known as input and output slack variables, respectively, and are optimized in a second phase, where \( \theta^* \) is the optimal radial contraction computed from the initial phase (3.4):

\[
\max \quad w = \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+
\]

**Subject to:**

\[
s_i^- = \theta^* x_{io} - \sum_{i=1}^{m} x_{ij} \lambda_j \quad (i = 1, \ldots, m)
\]

\[
s_i^+ = \sum_{r=1}^{s} y_{rj} \lambda_j - y_{ro} \quad (r = 1, \ldots, s)
\]

\[
\lambda_j \geq 0 \quad (j = 1, \ldots, n)
\]

\[
s_i^- \geq 0 \quad (i = 1, \ldots, m)
\]

\[
s_r^+ \geq 0 \quad (r = 1, \ldots, s)
\]
Existence of slack represents mix inefficiency and therefore a DMU is fully technically
efficient if any only if $\theta^* = 1$ (radial efficiency) and $s^* = s^* = 0$ (zero slacks). However, if
only $\theta^* = 1$ with nonzero slacks then the DMU is radially efficient with mix inefficiencies.
An inefficient DMU can be improved by referring its inefficient behaviour to the efficient
frontier formed by $E_o$, the reference set of DMU, composed of efficient DMUs. This
improvement is a projection to the point ($\hat{x}_o, \hat{y}_o$) on the frontier where:

\[
\hat{x}_{io} = \theta^* x_{io} - s_i^- = \sum_{j \in E_o} x_{ij} \lambda_j^* \leq x_{io} \quad (i = 1, ..., m)
\]
\[
\hat{y}_{ro} = y_{ro} + s_r^+ = \sum_{j \in E_o} y_{rj} \lambda_j^* \geq y_{ro} \quad (r = 1, ..., s)
\]

($\hat{x}_o, \hat{y}_o$) are the coordinates of a virtual linear composite DMU (i.e. $\sum_{i} DMU_i \lambda_i$ where DMU_i’s
are efficient and $\lambda_i$ are proportionality weights for DMU_i) used to evaluate the performance
of DMU_o. It represents the target for efficient production that DMU_o should strive for
[COOP07].

Figure 3.1 presents a graphical overview of the CRS model. The CRS efficient frontier is
drawn from the origin and is shown with a solid line. Among all DMUs, only those are
considered efficient that are located on the efficient frontier. In this figure, DMU H is the
only DMU on the efficient frontier; hence, it is considered as an efficient DMU. Other
DMUs in the figure are considered inefficient.
3.2.2 Output-Oriented CRS Model

The output oriented CRS model aims to maximize outputs at the same observed input values. The primal and dual formulations are:

**CRS Output-Oriented Primal (3.8)**

Minimize \( \sum_{i=1}^{m} p_i x_{i0} \)

Subject to

\[ \sum_{r=1}^{s} q_r y_{ro} = 1 \]

\[ \sum_{r=1}^{s} q_r y_{rj} - \sum_{i=1}^{m} p_i x_{ij} \leq 0 \]

j = 1, ..., n

\( p_1, p_2, ..., p_m \geq 0 \)

\( q_1, q_2, ..., q_s \geq 0 \)

**CRS Output-Oriented Dual (3.9)**

Maximize \( \eta \)

Subject to

\[ x_{i0} \geq \sum_{j=1}^{n} x_{ij} \mu_j \]

\[ \eta y_{ro} \leq \sum_{j=1}^{n} y_{rj} \mu_j \]

i = 1, ..., m

r = 1, ..., s

\( \mu_j \geq 0 \)

The input \( t^- \) and output \( t^+ \) slacks of the output-oriented model are calculated in a second phase:

\[ t^-_i = x_{i0} - \sum_{i=1}^{m} x_{ij} \mu_j \quad (i = 1, ..., m) \]  \hspace{1cm} (3.10)

\[ t^+_r = \sum_{r=1}^{s} y_{rj} \mu_j - \eta^* y_{ro} \quad (r = 1, ..., s) \]

Where \( \eta^* \) is the optimal expansion from the first phase and \( t^- = \frac{s^-}{0^+} \) and \( t^+ = \frac{s^+}{0^-} \).

A DMU is CRS fully efficient if and only if \( \eta^* = 1 \) and all optimal slacks are zero. For inefficient DMUs, the following CRS projection can be used to improve \((\hat{x}_o, \hat{y}_o)\):

\[ \hat{x}_{i0} = x_{i0} - t^-_i \quad (i = 1, ..., m) \]  \hspace{1cm} (3.11)

\[ \hat{y}_{i0} = \eta^* y_{ro} + t^+_r \quad (r = 1, ..., s) \]

3.3 Variable Returns-To-Scale (VRS) Model

The VRS model was first formulated by Banker, Charnes and Cooper in 1984 and provides variable returns-to-scale DEA formulation [BANK84]. The VRS model defines a piecewise linear convex efficient frontier composed of the best performing DMUs. In multiple inputs and outputs, the frontiers are encapsulated in a convex hull of efficient DMUs. The VRS model is formulated similarly to CRS but the addition of a variable \( (\tilde{u}_o) \) to the model,
accounts for the economies of scale. In cases that a unique optimal solution is present, \( \bar{u}_o < 0 \) shows that the units are operating under increasing returns-to-scale while \( \bar{u}_o = 0 \) indicates constant returns-to-scale and \( \bar{u}_o > 0 \) indicates decreasing returns-to-scale.

### 3.3.1 Input Oriented VRS Model

Equation (3.12) below depicts the formulation of input oriented VRS model where efficiency scores \( \theta \) of \( n \) units are maximized:

\[
\text{Maximize } \theta = \frac{\sum_{r=1}^{s} u_r y_{ro} - \bar{u}_o}{\sum_{i=1}^{m} v_ix_{io}} \tag{3.12}
\]

Subject to:

\[
\frac{\sum_{r=1}^{s} u_r y_{rj} - \bar{u}_o}{\sum_{i=1}^{m} v_ix_{ij}} \leq 1, j = 1, \ldots, n
\]

\[
u_r \geq 0; r = 1, \ldots, s
\]

\[
v_i \geq 0; i = 1, \ldots, m
\]

\[
\bar{u}_o: \text{free in sign}
\]

Like the CRS model, the above fractional VRS model can be transformed into more convenient computational forms: the primal and dual formulations. The major difference between CRS dual (eq.3.5) and VRS dual formulations is that the sum of \( \lambda_j \) variables must equal one.

<table>
<thead>
<tr>
<th>VRS Input-Oriented Primal (3.13)</th>
<th>VRS Input-Oriented Dual (3.14)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximize ( z = \sum_{r=1}^{s} u_r y_{ro} - \bar{u}_o )</td>
<td>Minimize ( \theta_{\text{VRS}} )</td>
</tr>
<tr>
<td>Subject to ( \sum_{i=1}^{m} v_ix_{io} = 1 )</td>
<td>Subject to ( \theta_{\text{VRS}x_{io}} \geq \sum_{j=1}^{n} x_{ij}\lambda_j )</td>
</tr>
<tr>
<td>( \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_ix_{ij} - \bar{u}_o \leq 0 )</td>
<td>( y_{ro} \leq \sum_{j=1}^{n} y_{rj}\lambda_j )</td>
</tr>
<tr>
<td>( j = 1, \ldots, n )</td>
<td>( \sum_{j=1}^{n} \lambda_j = 1 \ (\lambda_j \geq 0) )</td>
</tr>
<tr>
<td>( u_r, v_i \geq 0 )</td>
<td>( i = 1, \ldots, m )</td>
</tr>
<tr>
<td>( \bar{u}_o: \text{free in sign} )</td>
<td>( r = 1, \ldots, s )</td>
</tr>
</tbody>
</table>
As previously demonstrated, slacks (3.6) can be incorporated in a second phase to measure mix inefficiencies:

\[
s_i^- = \theta_{\text{VRS}} x_{i0} - \sum_{j=1}^{m} x_{ij} \lambda_j \quad (i = 1, \ldots, m)
\]
\[
s_r^+ = \sum_{i=1}^{n} y_{ir} \lambda_j - y_{ro} \quad (r = 1, \ldots, s)
\]

(3.15)

A DMU is VRS–efficient if and only if \(\theta_{\text{VRS}} = 1\) and has zero slacks (\(s^+ = s^- = 0\)). The target projection can be obtained by \((\hat{x}_0, \hat{y}_0)\):

\[
\hat{x}_{i0} = \theta_{\text{VRS}} x_{i0} - s_i^- \quad (i = 1, \ldots, m)
\]
\[
\hat{y}_{r0} = y_{ro} + s_r^+ \quad (r = 1, \ldots, s)
\]

(3.16)

The only difference between the VRS and CRS model is the addition of the convexity constraint \(\sum_{j=1}^{n} \lambda_j = 1\), and the variable \(\bar{u}_o\) for the dual formulation. This constraint reduces the feasible region for the linear program from a convex cone defined by the DMUs to the convex hull covering all the DMUs, thereby increasing the number of efficient DMUs [CHAR94]. Figure 3.2 depicts the graphical representation of the VRS model in comparison to the CRS model.

Figure 3.2 Graphical representation of CRS and VRS models
3.3.2 Output Oriented VRS Model

The primal and dual formulations of the output-oriented VRS models are as following:

**VRS Output-Oriented Primal (3.17)**

Minimize  
\[ z = \sum_{i=1}^{m} v_i x_{i0} - \bar{\eta}_o \]

Subject to  
\[ \sum_{r=1}^{s} u_r y_{ro} = 1 \]
\[ \sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} - v_o \geq 0 \]
\[ j = 1, \ldots, n \]
\[ p_i, q_r \geq 0 \]
\[ \bar{\eta}_o: \text{free in sign} \]

**VRS Output Oriented Dual (3.18)**

Maximize  
\[ \eta_{VRS} \]

Subject to  
\[ x_{i0} \geq \sum_{j=1}^{n} x_{ij} \lambda_j \]
\[ \eta_{VRS} y_{ro} \leq \sum_{j=1}^{n} y_{rj} \lambda_j \]
\[ i = 1, \ldots, m \]
\[ r = 1, \ldots, s \]
\[ \sum_{j=1}^{n} \lambda_j = 1 (\lambda_j \geq 0) \]

\( \eta_{VRS} \) is the proportional augmentation in all of the outputs that represents technical, radial efficiency, while \( \bar{\eta}_o \) is the unrestricted dual variable associated with the convexity constraint in the primal problem.

Again, slacks are accounted for in the second phase after maximal augmentation of \( \eta_{VRS} \) :

\[ t_i^- = x_{i0} - \sum_{i=1}^{m} x_{ij} \lambda_j \quad (i = 1, \ldots, m) \]  \( (3.19) \)

\[ t_r^+ = \sum_{r=1}^{s} y_{rj} \lambda_j - \eta_{VRS} y_{ro} \quad (r = 1, \ldots, s) \]

A DMU is VRS–efficient if and only if \( \eta_{VRS}^* = 1 \) and \( t^- = t^+ = 0 \), while an inefficient DMU can be improved with the following projection:

\[ \hat{x}_{i0} = x_{i0} - t_i^- \quad (i = 1, \ldots, m) \]  \( (3.20) \)

\[ \hat{y}_{i0} = \eta_{VRS}^* y_{ro} + t_r^+ \quad (r = 1, \ldots, s) \]

3.4 Slacks Based Model (SBM)

An extension of the VRS and CRS model is the slack based measure of efficiency model (SBM). While both VRS and CRS models require a distinction between input and output orientation, the SBM model combines both orientations to simultaneously reduce the inputs and increase the outputs by only taking the slacks into account when measuring efficiency.
Subject to

\[
\sum_{j=1}^{n} x_{ij} \lambda_j + s_i^- = x_{io} \quad (i = 1, \ldots, m)
\]

\[
\sum_{j=1}^{n} y_{rj} \lambda_j - s_r^+ = y_{ro} \quad (r = 1, \ldots, s)
\]

\[
\lambda_j, s_i^-, s_r^+ \geq 0
\]

Where \( 0 \leq \rho \leq 1 \)

A DMU is SBM efficient when \( \rho^* = 1 \) (zero slacks). Inefficient DMUs can be improved by the following projection \((\hat{x}_o, \hat{y}_o)\):

\[
\hat{x}_o = x_{io} - s_i^- \quad (i = 1, \ldots, m)
\]

\[
\hat{y}_o = y_{ro} + s_r^+ \quad (r = 1, \ldots, s)
\]

3.5 DEA Extensions

After the introduction of the DEA method, several modifications have been developed to improve a model’s accuracy and to be able to more closely represent a real situation. Such concepts include categorical and non-discretionary variables and multiplier constraints, as discussed below.

3.5.1 Categorical and Non-discretionary (Non-controllable) Variables

In order to accurately represent the production process of a DMU with DEA, some inputs and outputs may still need to be incorporated even though they are not controllable by management. Such variables are referred to as Non-Discretionary variables. For instance, the
surrounding geographical environment of the DMU is not something that management can control, however such geographical factors do have an impact on productivity levels as it is related to the economic status of the area as well as other geographical characteristics that may affect the DMU’s performance. Studies, including Banker et al. [BANK86a], expanded DEA models to include exogenously fixed variables and segmented the DEA models to group similar DMUs that operate in comparable environments for comparisons. Banker et al. [BANK86b] also proposed to include categorical variables, factors that can only take two or more discrete values, to help define the branch more accurately among its peers. Examples of categorical variables include the presence of ATM units, the number of teams working in the CSR, weekend opening availability of branches, and more as they were included to insure that each DMU’s efficiency is measured only against those DMUs operating under the same conditions and environment.

3.5.2 Multiplier Constraints

DEA assigns multipliers to each DMU’s input and output variables such that the DMU looks the best it can. However such theoretical results do not necessarily translate into the real situation. To increase the accuracy of the model, multiplier restrictions based on managerial and organizational factors can be integrated into the model to represent the realistic restrictions on the inputs and outputs.

Such a constraint approach was introduced in 1988 by Dyson et al. [DYSO88], imposing upper and lower boundaries on each multiplier. In 1989, Charnes et al. [CHAR89] introduced the Cone-Ratio Method to restrict the feasible regions of various multipliers to given closed cones, defined by non-negative directional vectors. Furthermore, Thompson et al. in 1990 introduced the Assurance Region method to enforce limits on ratios of multipliers [THOM90]. This method is particularly useful when the specific values of the variable(s) are unknown but a general range of values is known. The constraints take the form of in the multiplier formulation (3.23):

\[
L_{1,2} \leq \frac{v_2}{v_1} \leq U_{1,2}
\]

(3.23)
3.6 Technical and Scale Efficiency

DEA results include technical and scale efficiency, target projections for the DMUs, as well as their returns-to-scale’s level of operation, which all are essential information for the analysis.

The CRS DEA model assumes a constant returns-to-scale (CRS) production for the DMUs, meaning that scale of production does not affect efficiency. Hence, it only considers one efficiency score, called the overall technical efficiency. The VRS DEA model assumes variable returns-to-scale (VRS) production for the DMUs, measuring both scale efficiency and technical efficiency. Scale Efficiency measures each DMUs distance from its optimal scale size, by dividing the CRS efficiency by the VRS efficiency.

Figure 3.2 shows technical efficiency and scale efficiency concepts for both CRS and VRS DEA models. The dashed line from the origin is representing the CRS frontier and the solid line is showing the VRS frontier.

DMU G is located on both efficiency frontiers. It is CRS efficient as it is the only producer on the CRS frontier. It also exhibits the highest average productivity, i.e., highest output per input or slope, for its given input and output mix. Therefore, G is referred to as an efficient DMU that is operating at its most productive scale size (MPSS) [BANK84]. VRS Frontier (solid line) is built on DMUs: F, G, H, and I. All these DMUs are technically efficient, however, only G is scale efficient, as it is the only DMU that is operating at constant returns-to-scale. Therefore, G is considered both technically efficient and scale efficient, operating at the MPSS. Cooper et al. [COOP07] provides a detailed explanation of MPSS term.
3.7 DEA Characteristics

3.7.1 Advantages

DEA has several strengths over other analytical tools commonly used in performance measurement, such as regression and ratio analyses. These strengths include that:

- DEA does not require any prior assumption regarding the functional form relating inputs and outputs
- DEA is able to simultaneously handle multiple inputs and multiple outputs
- DEA’s inputs and outputs do not need to have consistent metrics
- DEA compares DMUs with a peer or combination of peers
- DEA produces a single all-encompassing efficiency score that characterizes a unit’s production of all relevant outputs

3.7.2 Disadvantages

With DEA’s flexibility and its unique ability to form an empirical frontier, DEA still has limitations that users should be aware. These limitations include:

- DEA does not account for random error and such error may lead to an inaccurate result
- DEA is unable to accurately model small sample sizes
- DEA only provides a relative efficiency score, not a theoretical frontier
- If is retrospective and future projections are not available
CHAPTER 4:

BANK’S CURRENT MODEL (BCM) AND DATA OVERVIEW

This chapter provides an overview of the Bank and the BCM. The Bank under study employs a complex staff allocation model based on a queuing algorithm, to estimate the sufficient number of CSR employees for each branch on an annual basis. This section elaborates on BCM and presents statistical analysis performed on the data set to fully understand the properties and characteristics of the data and to determine suitable variables for the DEA models (Chapter 5 and Chapter 6).

4.1 Bank Overview

The collaborating Bank under study is one of the ‘Big Five’ Canadian banks, currently ranked in the top 100 banks worldwide in terms of asset size [CANA03]. The Bank offers an extensive range of financial products and services to customers globally, including personal, commercial and corporate banking, and other financial and investment services. Table 4.1 provides a partial list of the products and services that the Bank offers. These products are offered through different delivery channels, including the branch, ABM, debit cards, internet banking and telephone banking.

Table 4.1 Bank’s Personal and Business Products and Services

<table>
<thead>
<tr>
<th>Personal and Business Products and Services</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>• Bank Accounts</td>
<td>• Investments</td>
</tr>
<tr>
<td>• Lines of Credit</td>
<td>• Credit Cards</td>
</tr>
<tr>
<td>• Online Banking and trading</td>
<td>• Mortgages</td>
</tr>
<tr>
<td>• Foreign Exchange</td>
<td>• Loans</td>
</tr>
<tr>
<td>• Brokerage</td>
<td>• Mutual Funds</td>
</tr>
</tbody>
</table>
4.2. Data Overview

The focus of this study is the Customer Service Representative (CSR) team of the Bank’s branch network. CSRs are responsible for all direct over-the-counter (OTC) transactions that occur in a branch. They are commonly referred to as ‘tellers’ and are constantly interacting with customers. The CSR team typically performs three distinct roles. CSR provide professional services to clients with predominantly transactional banking needs. Central Tellers (CT) provide personal and business clients with professional service for all their cash handling and transactional banking needs. Finally, Client Service Representatives Experts (CSR:Expert) handle complex transactions, such as foreign exchange, for all clients. The data used in this study was sourced from the initial pool of over 1200 branches the bank owns. However, this data set was later reduced to 1166 branches, after eliminating irregularities, missing information, commercial branches and branches without tellers. The remaining dataset includes information on branch characteristics, including market, geographic region, branch size, total number of employees, weekly average transaction and more, as listed on Table 4.2.

### Table 4.2 List of Data provided by the Bank on their National Branch Network

<table>
<thead>
<tr>
<th>Categorical</th>
<th>Numerical</th>
<th>Historical Data</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Branch Background</strong></td>
<td><strong>Bank’s Current Model Data</strong></td>
<td><strong>Historical Data</strong></td>
</tr>
<tr>
<td>Region</td>
<td>Number of weekly sessions by branch by team</td>
<td>Average weekly number of total transactions</td>
</tr>
<tr>
<td>Market</td>
<td>CSR FTE requirement by team</td>
<td>Average weekly number of business transactions</td>
</tr>
<tr>
<td>Distribution</td>
<td>Model Levers</td>
<td>Average transaction time (min)</td>
</tr>
<tr>
<td>Footprint</td>
<td>Model serve time</td>
<td>Paid CSR FTE by team</td>
</tr>
<tr>
<td>Branch size</td>
<td>Model wait time</td>
<td></td>
</tr>
<tr>
<td><strong>Hours and Days Availability</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Saturday open</td>
<td># of teams</td>
<td></td>
</tr>
<tr>
<td># of days open</td>
<td># of mapped assets</td>
<td></td>
</tr>
<tr>
<td>Weekday protocol</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
4.3 The Bank’s Current Staff Allocation Model (BCM) Overview

This section provides an overview of the BCM including the overall managerial decision making process and the performance ratios used by the Bank.

4.3.1 Definitions

A *Transaction Time* starts when a client approaches the counter and swipes their card to initiate a transaction and ends when the transaction finishes as the account is closed by the teller in the system. Such a method of collecting transaction times may incur some potential errors if an employee forgets to close the account in between transactions.

*Full Time Equivalent* (FTE) represents one full time employee’s base hours of work in a week, which is 37.5 hours/week. In this study, FTE is used to measure the amount of human resource units needed for branch operations.

4.3.2 CSR Resource Allocation Process

The CSR resource allocation process involves a complex model as well as management’s input to prescribe appropriate resource deployment to each branch. Such a process is a cycle where the Bank’s model uses historical transaction volume data and other model levers to estimate the optimum FTE per branch by team, which then goes under management’s adjustments to add in other factors, such as coverage, to determine the Net FTE by branch. Such Net FTE is then used to determine the final maximum number of approved FTEs per branch and this cycle completes when the actual paid FTE data (Paid Data) enters their internal data server with other information including transaction time and number of transactions. As shown in Figure 4.1, it completes the cycle as the model uses the updated historical data to re-calculate the optimum resource distribution for the next season.
4.3.3 The Bank’s Current Model

The Bank currently utilizes a commercially available product (BCM) calibrated to the Bank’s objectives, to determine the optimum count of FTE for each CSR team by branch. Since the BCM under study is commercial software, it is considered as a black box model that uses the following model levers and inputs to produce the outputs as shown on Table 4.3.

The BCM recommends each branch with a required FTE by team such as CSR, CSR:Expert and CT according to previously designated number of teams by the corporate management. The BCM uses historical transaction volumes and corporate management’s designated inputs, such as desired serve time (minutes), to estimate the transaction volume and thus recommend the FTE count required to service the volume under a desired transactional time for each branch.

*Desired serve time* (minutes) is the desired average transactional time for the corresponding branch as decided by corporate management.
Table 4.3 List of Inputs, Outputs and Model Levers for the Bank’s Current staff allocation Model (BCM)

<table>
<thead>
<tr>
<th>Model Inputs</th>
<th>Model Levers (management inputs)</th>
<th>Model Output</th>
</tr>
</thead>
</table>
| • Historical volume data (# of transactions) | • Desired Serve Time  
• Wait Time  
• # of Teams  
• # of mapped Assets | • Required FTE |

*Wait time* is the benchmark that the Bank aims to meet and it is another key model lever used to determine the FTE count. It is based on the percent of transactions that were completed under certain amount of time. The Bank currently aims to complete 85% of transactions under either 5 minutes (85/5) or 10 minutes (85/10) depending on branch characteristics. In fact, 70% of the branches currently operate under the 85/5 benchmark and only smaller branches operate under 85/10 benchmarks. Smaller branches are targeted with this more lenient benchmark since all branches require a minimum number of employees to function as a branch and the 85/5 benchmark may be a burden to smaller branches, which do not require all that many dedicated representatives as CSRs for the amount of transaction volume.

There are a maximum of 3 teams under the CSR group. As the number of teams grows, the responsibility of the CSRs gets divided into CSR, CSR:Expert and CT teams. Seventy five percent of the branches operate under one team and thus all transactional activities are accounted concurrently. When there is more than one team of CSR groups, the CSR:Expert takes charge of more complex transactions, such as foreign exchange, and CT takes charge of business transactions and cash management.

Model levers also include the number of mapped assets which represents the number of computer stations connected to the Bank’s internal server and are available to perform transactions. However, the number of mapped assets was not considered in this study since it shouldn’t be a restricting factor in optimizing human resource allocation. More assets can be stationed upon the need of each branch.
4.3.4 Bank’s Current Performance Measurement Ratios

The Bank mainly uses the following two ratios to measure the efficiency of the CSR teams’ performance by branch. They are Throughput ratio and Client Service ratio, calculated as the following (Equations 4.1, 4.2, 4.3 and 4.4 in order):

\[
\text{Throughput}_{\text{paid}} = \frac{\text{# of Avg weekly transactions}}{\text{Total Paid FTE}} \quad (4.1)
\]

\[
\text{Throughput}_{\text{rec}} = \frac{\text{# of Avg weekly transactions}}{\text{Net Recommended FTE}} \quad (4.2)
\]

Total Paid FTE is the actual paid FTE count for the branch and the Net Recommended FTE is the BCM recommended FTE count for the branch. Throughput demonstrates the branch’s performance by calculating the average number of transactions completed by one FTE at a branch and Client Service ratio demonstrates the branch’s performance by calculating the average percent of time one FTE spends interacting with customers to complete transactions. Total Transaction Time is measured in minutes and it is the total amount of transaction time clocked in a week for the branch.

\[
\text{Client Service Ratio}_{\text{paid}} = \frac{\text{Total Transaction Time}}{\text{Total Paid FTE} \times 37.5 \text{ hours/\text{FTE} } \times \frac{60 \text{ min}}{\text{hour}}} \quad (4.3)
\]

\[
\text{Client Service Ratio}_{\text{rec}} = \frac{\text{Total Transaction Time}}{\text{Net Recommended FTE} \times 37.5 \text{ hours/\text{FTE} } \times \frac{60 \text{ min}}{\text{hour}}} \quad (4.4)
\]

The Bank uses the above two ratios to compare the actual paid FTE data and BCM’s recommended FTE data, and also to overview the changes over the year. However such one dimensional ratio analysis does not clearly indicate the efficiency of the branch network as explored in the literature review (Section 2.1). For instance, all branches require a certain minimum number of FTEs to operate even if all resources are not fully used to meet the transactional volume demand. Such a discrepancy cannot be accounted for in the above ratio
analyses and discriminate against smaller branches in comparison to larger branches. Further analysis on the performance ratios is performed in Section 5.6.

The Bank also aims to complete certain percentage of the total transactions under certain time to ensure prompt services and to set a goal for the CSR team to reduce wait time while increasing face time. Such a benchmark can be calculated as follows (Equation 4.5):

\[
\frac{\text{% of Transactions meeting benchmark}}{\text{of Transactions under } x \text{ minutes (benchmark)}} = \frac{\text{# of Transactions under } x \text{ minutes (benchmark)}}{\text{# of Total Transaction}}
\] (4.5)

Mainly there are two benchmarks desired by the Bank and they are 85% of transactions completed under 5 minutes of transaction time and 85% of transactions complete under 10 minutes of transaction time.

### 4.4 Data Overview: Univariate Analysis

Univariate analysis of the dataset was performed to clarify and understand data characteristics and to identify significant variables to be used in the DEA models. There are 8 geographical regions in total and 1166 branches are distributed across these regions, as can be seen in Figure 4.2, with slightly less population in region 2 and 3. On average, each region has about 145 branches with a standard deviation of 26 branches.

![Figure 4.2 Distribution of Branches across different Geographic Regions](image)
The Bank subdivides its branches into five different groups according to their size; i.e. ‘Extra Small’, ‘Small’, ‘Medium’, ‘Large’ and ‘Extra Large’. About half of the branches are classified as ‘Medium’ size branches while ‘Extra small’ and larger branch size groups have much less in units as can be seen from the distribution on Figure 4.3. Such grouping solely depends on the number of total employees working at the branch and ‘Medium’ size has the largest bracket allowing more number of branches to fall under this category. Branch size grouping is important in the proposed DEA models to group similar units, since the national branch network has a wide range of branch size and different minimum requirements needed for different sizes. Thus this study reclassified the Bank’s branch network into four branch size categories such as ‘Small’, ‘Medium – Small’, ‘Medium – Large’, and ‘Large’ using the segmentation tool provided by a commercially available DEA software, EPO from Alta Bering.

The new segmentation was done using three different variables to define the size of the branch: total number of employees per branch, average weekly transaction volume per branch and average weekly business transaction volume per branch. The new segmentation resulted in a fairer distribution across different branch size groups, as can be seen in Figure 4.4. On average there are 292 branches in each size group with a standard deviation of 132 branches. ‘Large’ branch size group still showed significantly lower number of units however, this is because the Bank’s branch network has significantly lower number of branches with such large operations.

Figure 4.3 Distribution of Branches by Bank’s Branch Size Group
Total FTE by branch showed a log-normal distribution with slight skewness to the left with an average of 13.5 FTE and a standard deviation of 6.7 FTE. The distribution can be seen in Figure 4.5.

Average weekly number of transactions by branch and average weekly number of business transactions by branch both showed a log-normal distribution skewed to the left, with an average number of transactions of 1583 and 313 respectively. The distributions can be seen in Figure 4.5.
in Figures 4.6 and 4.7 respectively. Not surprisingly, the average weekly number of transactions by branch had a strong correlation to the Total FTE by branch with a correlation coefficient value of 0.92. Total transaction volume also had a strong correlation to the business transaction volume with a correlation coefficient value of 0.81. Average business transaction volume had a significant yet weaker correlation with the Total FTE by branch with a correlation coefficient value of 0.67.

Figure 4.6 Distribution of average # of weekly total transactions by branch

![Distribution of Average weekly # of Transaction by Branch](image)

Figure 4.7 Distribution of average weekly # of business transactions by branch

![Distribution of average weekly # of Business Transaction by Branch](image)
Lastly, there are 5 different desired serve times ranging from 3 minutes to 5 minutes for every 0.5 minute interval. As demonstrated in Figure 4.8, the majority of the branches are desired to complete transactions under 5 minutes. The average number of branches in each desired serve time group is 233 branches.

Figure 4.8 Distribution of branches by desired serve time

![Distribution of Branches by Desired Serve Time](image)
CHAPTER 5:

DEA MODEL #1 FORMULATION AND RESULTS: EVALUATING BCM’S PERFORMANCE

This chapter provides an overview of the Data Envelopment Analysis (DEA) model proposed to evaluate the staff allocating model of the Bank under study. The Bank uses a black box model (BCM) that corporate management uses to allocate the required FTE for the CSR teams across their national branch network. In this study, DEA is used to develop an evaluation system to validate the staffing allocation across the Bank’s branch network and to evaluate the performance of the model and the branches. To evaluate the BCM, this chapter constructed a DEA model to best represent the network of resources and their relationship to the outputs. The input oriented DEA model was employed since inputs are much more controllable than the outputs in the given industry setting.

This section discusses the concepts and definitions of the proposed DEA models; i.e. the inputs, outputs and non-controllable variables used. Furthermore, a summary of the results of the DEA analysis is provided with information including the CRS and VRS scores, as well as the results of the local geographical and branch size comparisons.

5.1 Data Employed

The focus of this study is on the evaluation of managing CSR allocations across the Bank’s branch network. The Bank under study provided the data for this study. After eliminating large commercial, teller-less branches as well as missing information and irregularities, the total number of branches under study was reduced from over 1200 to 1166. Branch information is further subdivided into four major branch size groups: ‘Small’, ‘Medium-Small’, ‘Medium-Large’ and ‘Large’ according to three variables that could classify a branch’s size (Section 4.4).
5.2 Model Formulation: Evaluating the BCM’s performance

The goal of this DEA model is to examine the efficiency of the BCM by looking at staff efficiency and allocation of FTEs for the corresponding CSR teams, so that the branch would be able to complete the same volume of transactions with fewer FTEs than before. Therefore, an input oriented model was employed to reduce the number of FTEs to produce the same volume of transactions.

An important step in the efficiency analysis lies with defining the input and output variables. The inputs of this DEA model consisted of BCM’s recommended FTE count by team (CSR, CSR:Expert, CT) and the outputs of this model consisted of the average weekly number of personal client transactions calculated over the year and the average weekly number of business client transactions calculated over the year (two values that define the demand for branch work throughout the year). There are other variables that also affect the use of branch resources and they are branch size, desired serve time, wait time, and number of teams. These variables were included in the model as non-controllable inputs since, although they have an effect in the use of resources and producing transactions, they are not controllable by the bank, hence, cannot be included in the BCM. The following describes the non-controllable inputs used in the model in detail:

- **Branch Size:** the total number of employees at the branch varied quite widely; hence, it was essential to differentiate the branches in terms of their size, so that each branch would only be compared against those similar to it.

- **Desired Serve Time:** the desired serve time ranged from 3 to 5 minutes and it is designated by the corporate management for each branch as to what the desired average transaction time is and thus would affect the staffing of each branch.

- **Wait Time:** the wait time is the benchmark of meeting 85% transactions under a certain amount of minutes where this varied from 5 minutes to 10 minutes and the difference between two benchmarks would result in higher staffing for the 85/5 benchmarked branch.
• **Number of Teams**: the number of subdivided CSR teams such as whether all CSR, CSR:Expert and CT are present in each branch.

Branch size helps DEA to group similar branches according to similar branch environment. Desired serve time, wait time and number of teams are key model levers for the BCM and they are designated by corporate management to provide different expectations for each branch. Such information is crucial when comparing similar branches with same expectations. Figure 5.1 summarizes the input and output variables for this DEA model.

**Figure 5.1 Model #1: List of Inputs, Outputs and Non-controllable variables**

<table>
<thead>
<tr>
<th>Inputs</th>
<th>Non-Controlable Variables</th>
<th>Outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCM Recommended:</td>
<td>• Branch Size</td>
<td>• Average weekly # of personal transactions</td>
</tr>
<tr>
<td>• CSR FTE count</td>
<td>• Desired serve time (min)</td>
<td>• Average weekly # of business transactions</td>
</tr>
<tr>
<td>• CSR:Expert FTE Count</td>
<td>• Model wait time</td>
<td></td>
</tr>
<tr>
<td>• CT FTE Count</td>
<td>• Number of teams</td>
<td></td>
</tr>
</tbody>
</table>

With 3 inputs, 2 outputs and 4 non-controllable variables, a sufficient number of DMUs required for this study is a minimum 15 DMUs as discussed in Section 3.1. The group of DMUs for this study includes almost all the branches of the Bank across Canada, 1166 branches (DMUs), and thus is sufficient for this model.

### 5.3 Empirical Findings

Microsoft Access 2007 and Microsoft Excel 2007 were employed to perform statistical analysis and build the final data set. The computer software, DEA-Solver-Pro Version 5.0, was used to run the DEA models and it was purchased from SAITECH, Inc. It is a Microsoft Excel macro designed on the basis of the textbook “Data Envelopment Analysis – A Comprehensive Text with Models, Applications, References and DEA-Solver Software” written by Cooper, Seiford and Tone in 2007 [COOP07]. Therefore, both input data files and results generated by DEA-Solver-Pro were in excel spreadsheet forms. Both non-

\[ n \geq \max\{m \times s, 3(m + s)\} \rightarrow n \geq \max\{3 \times 2,3(3 + 2)\} \rightarrow n \geq \max\{6,15\} \rightarrow n \geq 15 \]
controllable CRS Input oriented “NCN-C-I” and non-controllable VRS Input oriented “NCN-V-I” were used in this study.

A three-part analysis was performed on the result. In the first part, a CRS input oriented DEA model, as well as the VRS input oriented DEA model, were employed to evaluate the efficiency of the entire sample of the bank branches. In the second part, both CRS and VRS input oriented results were grouped by branch size to explore the performance differences between different branch size groups. In the third part, both CRS and VRS input oriented model results were grouped by geographical regions to explore significant regional differences observed from the model.

5.3.1 Model #1: Result for All Branches

In the first run, CRS and VRS input oriented DEA models were used to calculate the relative efficiencies of the 1166 branches across Canada. 154 branches were found to be CRS efficient (efficiency =1) and 174 branches were found to be VRS efficient; i.e. approximately 15% of the network were discovered to be DEA efficient. The overall average of the CRS efficiency was 72.4% with a standard deviation of 20.7% and the VRS efficiency showed a similar result and displayed 73.4% average efficiency score with a standard deviation of 20.9%. Since the ratio of the CRS and the VRS efficiency score is close to 1(Scale Efficiency), one can conclude that the Bank’s process is actually a natural CRS process [TOCH06]. The summary of CRS and VRS results for all branches, as well as the frequency distribution of the two models, are presented in Table 5.1 and Figure 5.2 respectively.

As expected from one of the large banks in Canada, the distribution of the efficiency score is skewed to the right with significant cluster of branches with efficiency score of 1.0. It is important to note that the DEA still was able to distinguish high performing branches from the inefficient branches as the efficiency score ranged from 18% to the fully efficient, 100%. The branches that are in the lower bracket of the efficiency distribution should be reviewed by management to reveal sources of potential improvement in resource allocation.
Table 5.1 Model #1: CRS and VRS DEA Model Results for All Branches

<table>
<thead>
<tr>
<th>DEA Model</th>
<th>CRS Input-Oriented</th>
<th>VRS Input-Oriented</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of DMUs</td>
<td>1166</td>
<td>1166</td>
</tr>
<tr>
<td>Number of Efficient DMUs</td>
<td>154</td>
<td>174</td>
</tr>
<tr>
<td>Average Efficiency Score</td>
<td>72.4%</td>
<td>73.4%</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>20.7%</td>
<td>20.9%</td>
</tr>
<tr>
<td>Maximum Efficiency Score</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Minimum Efficiency Score</td>
<td>18.2%</td>
<td>18.2%</td>
</tr>
</tbody>
</table>

Figure 5.2 Model #1: CRS and VRS Efficiency Distribution for All Branches

5.3.2 Model #1: Result grouped by Branch Size groups

The summary of CRS and VRS average efficiency distribution and scores grouped by the branch size groups is illustrated in Figure 5.3. When the DMUs were grouped by their branch size, the ‘Large’ group had the highest average efficiency score, with 0.94, while the ‘Medium-Small’ group had the lowest average efficiency score of 0.61. This information can be used in the Bank’s management setting to further investigate the efficiency of the BCM for ‘Medium-Small’ branches and identify any shortcomings particular for that size group. Of course, it could also be that these branches do well, but because of minimum staffing and
limited incoming business, they show worse performance than they deserve. But, an investigation would bring this out too.

**Figure 5.3 Model #1: CRS and VRS Average Efficiency Distribution by Branch Size for All Branches**

![Figure 5.3 Model #1: CRS and VRS Average Efficiency Distribution by Branch Size for All Branches](image)

**5.3.3 Model #1: Result grouped by Geographic Regions**

The summary of CRS and VRS average efficiency distribution and scores by the geographic regions is illustrated in Figure 5.4. When the DMUs were grouped by their geographic regions, region 5 displayed the highest average efficiency score of 0.78 while region 3 had the lowest average efficiency score of 0.65. The average efficiency score did not show a significant difference between different regions, indicating consistent performance levels across Canada without regional differences affecting the model. However, the region with the lowest efficiency score, region 3, may be affected by other environmental factors not consistent in other regions and should be considered within BCM to increase efficiency of the staff allocation for that region. Such a capability is not available in the BCM, but DEA is able to estimate target changes for inputs and outputs and thus, determine directions of improvement for that particular region by analyzing the result of this proposed DEA model.
5.3.4 Comparison between Paid FTE and BCM Recommended FTE

Building on the previous DEA model, another model based on the actual paid FTE value was built to measure the potential efficiency gain by the BCM recommendation when compared to the actual FTE input that was used to produce the number of transactions in the historical data. For this model, actual paid FTE counts by CSR team (CSR, CT, CSR:Expert) were used as input variables, so that the corresponding DEA result can be compared with the BCM recommended DEA result (Model #1).

Figure 5.5 Actual Paid Model: List of Inputs, Outputs and Non-controllable variables
The summary of CRS input oriented result comparison is shown in Table 5.2. Overall, BCM recommended FTE’s DEA average efficiency is very similar to the actual paid FTE’s DEA average efficiency with a difference of only 0.8%. This result indicated that the bank branches are performing close to the Bank’s corporate management’s recommendations (BCM).

Table 5.2 CRS DEA Model Result Comparison for Actual Paid model vs. BCM Recommended (Model #1)

<table>
<thead>
<tr>
<th>CRS DEA Result: From Actual Paid FTE Data</th>
<th>CRS DEA Result: From BCM FTE Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Inputs</td>
<td>3</td>
</tr>
<tr>
<td>No. of Outputs</td>
<td>2</td>
</tr>
<tr>
<td>No. of Non-controllable</td>
<td>6</td>
</tr>
<tr>
<td>No. of DMUs</td>
<td>1166</td>
</tr>
<tr>
<td>No. of efficient DMUs</td>
<td>289</td>
</tr>
<tr>
<td>Average</td>
<td>71.8%</td>
</tr>
<tr>
<td>SD</td>
<td>22.9%</td>
</tr>
<tr>
<td>Maximum</td>
<td>100%</td>
</tr>
<tr>
<td>Minimum</td>
<td>14.0%</td>
</tr>
<tr>
<td></td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>1166</td>
</tr>
<tr>
<td></td>
<td>154</td>
</tr>
<tr>
<td></td>
<td>73.40%</td>
</tr>
<tr>
<td></td>
<td>20.70%</td>
</tr>
<tr>
<td></td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>18.20%</td>
</tr>
</tbody>
</table>

Table 5.3 CRS DEA Result Comparison Grouped by Branch Size: Actual Paid vs. BCM FTE (Model #1)

<table>
<thead>
<tr>
<th>BY SIZE</th>
<th>Average Efficiency Score (%)</th>
<th>CRS Result: From Paid FTE</th>
<th>CRS Results: From BCM FTE</th>
<th>% improvement by BCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>0.66</td>
<td>0.76</td>
<td>12.91%</td>
<td></td>
</tr>
<tr>
<td>Medium-Small</td>
<td>0.63</td>
<td>0.61</td>
<td>-2.28%</td>
<td></td>
</tr>
<tr>
<td>Medium-Large</td>
<td>0.83</td>
<td>0.77</td>
<td>-8.55%</td>
<td></td>
</tr>
<tr>
<td>Large</td>
<td>0.93</td>
<td>0.94</td>
<td>0.61%</td>
<td></td>
</tr>
<tr>
<td>Grand Average</td>
<td>0.72</td>
<td>0.72</td>
<td>0.81%</td>
<td></td>
</tr>
</tbody>
</table>

Actual paid count of FTE’s DEA efficiency score result was assessed in comparison to the BCM’s recommended FTE’s DEA efficiency score result for each branch. When DEA efficiency scores were summarized by branch size (Table 5.3) and by region (Table 5.4), the percentage of efficiency gain by the BCM FTE’s DEA efficiency did not show significant differences compared to the actual paid FTE’s DEA efficiency. However, certain groups
such as branch size ‘Small’, and regions 5 and 6 showed greater efficiency gain by the BCM DEA efficiency score, indicating potential improvement by the BCM’s recommendation for these groups of branches.

Table 5.4 CRS DEA Result Comparison Grouped by Region: Actual Paid vs. BCM Recommended (Model #1)

<table>
<thead>
<tr>
<th>Average Efficiency Score</th>
<th>CRS Result: From Paid FTE</th>
<th>CRS Result: From BCM FTE</th>
<th>% improvement by BCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.69</td>
<td>0.71</td>
<td>2.03%</td>
</tr>
<tr>
<td>2</td>
<td>0.73</td>
<td>0.71</td>
<td>-2.91%</td>
</tr>
<tr>
<td>3</td>
<td>0.68</td>
<td>0.65</td>
<td>-4.53%</td>
</tr>
<tr>
<td>4</td>
<td>0.77</td>
<td>0.77</td>
<td>-0.19%</td>
</tr>
<tr>
<td>5</td>
<td>0.74</td>
<td>0.78</td>
<td>4.74%</td>
</tr>
<tr>
<td>6</td>
<td>0.65</td>
<td>0.71</td>
<td>8.07%</td>
</tr>
<tr>
<td>7</td>
<td>0.75</td>
<td>0.70</td>
<td>-8.08%</td>
</tr>
<tr>
<td>8</td>
<td>0.71</td>
<td>0.74</td>
<td>2.95%</td>
</tr>
<tr>
<td>Grand Average</td>
<td>0.72</td>
<td>0.72</td>
<td>0.88%</td>
</tr>
</tbody>
</table>
5.4 Comparison with the Bank’s Performance Ratios

In this section, a DEA model was proposed to evaluate the BCM and the efficiency of the Bank’s national branch network. The following statistical analysis was performed to examine if there are any significant relationships between the obtained DEA efficiency scores and the Bank’s performance ratios, the Throughput and the Client Serve Ratios introduced in Section 4.3.4.

Throughput and Client Service ratios do not account for the minimum number of FTEs to operate a branch and discriminates against smaller sized branches. This discrimination can be seen from Figures 5.6 and 5.7 which plot the Client Serve ratio values and the Throughput ratio values against the branch size groups. There is a significant positive correlation between the branch size and the ratios as the simple regression analysis indicate medians of the two performance ratios display high correlation coefficient of 0.92 and 0.77 for Client Serve ratio and Throughput ratio. Such presence of correlation supports the weaknesses in using ratio analysis as efficiency measurements for the bank branches as discussed in literatures [FED03] [GI0K08].

Figure 5.8 and 5.9 plot the DEA efficiency score against the Client Serve Ratio and the Throughput ratio, respectively. As expected, the CRS DEA efficiency scores did not show significant correlation to the ratios, since no single ratio can appropriately represent the complex resource use in a branch. [FED03] Two ratios were compared to the DEA result in terms of comparing two different performance measurement tools for CSR staff allocation efficiency. Ideally, such comparison should result in a 45 degree line originating from (0,0) to show the correspondence in both of the measurement tools. However, while DEA attempts to incorporate different levels of operations in the model to evaluate, the ratios are one-dimensional and evaluate one aspect of the branch operation at a time. Such aspect is an important indicator of branch’s operation, however does not necessarily translate into the branch’s overall efficiency in terms of staff allocation. The difference in DEA result and the two performance ratios is a useful indicator for the management and they should consider the use of DEA to identify inefficient and efficient branches in terms of their performance ratios to compare the shortcomings of the current performance measurement ratios.
Figure 5.6 Distribution Client Serve Ratio by Branch Size Group

Client Serve Ratio value by Branch Size Group

- **Regression Equation**: $y = 0.0624x + 0.2854$
- **$R^2$ Value**: 0.8407

Figure 5.7 Distribution of Throughput Ratio by Branch Size Group

Throughput ratio value by Branch Size Group

- **Regression Equation**: $y = 23.236x + 229.54$
- **$R^2$ Value**: 0.5905
Figure 5.8 Comparison between CRS DEA Efficiency Score vs. Client Serve Ratio

Figure 5.9 Comparison between CRS DEA Efficiency score vs. Throughput Ratio
5.5 Chapter Summary

This chapter proposed a DEA model to evaluate the Bank’s Customer Service Representative (CSR) allocation model (BCM) by evaluating the efficiency of the Bank’s national branch network in the context of employment only (Figure 5.1). Branch level data provided by the Bank in this study was used to model input oriented CRS and VRS non-controllable variable DEA models. The summary of DEA’s CRS and VRS results are presented for the four branch size groups as well as by the geographic regions in Table 5.5.

As expected from one of the leading Banks in Canada, approximately 15% of the branches were efficient with a large percentage of the DMUs skewed to the right of the efficiency distribution. Overall, the group of ‘Large’ branches had the highest CRS and VRS average efficiency scores at 0.94. As for geographic regions, region 5 had the highest CRS and VRS average efficiency scores at 0.78 and 0.79, respectively. Average efficiency scores grouped by branch size and geographic regions ranged from 0.51 to 1.00 with the lowest average efficiency scores by region 3 ‘Medium – Small’ and region 6 ‘Medium- Small’ branches. In conclusion, with a large number of branches efficient and high average efficiency score of over 70% indicated that, in fact, the BCM is effective in allocating CSR resources across their national branch network.

Table 5.5 Model #1: Summary of CRS and VRS result by Branch Size and Region

<table>
<thead>
<tr>
<th>Region</th>
<th>Small</th>
<th>Medium-Small</th>
<th>Medium-Large</th>
<th>Large</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CRS</td>
<td>VRS</td>
<td>CRS</td>
<td>VRS</td>
</tr>
<tr>
<td>1</td>
<td>0.69</td>
<td>0.69</td>
<td>0.61</td>
<td>0.62</td>
</tr>
<tr>
<td>2</td>
<td>0.77</td>
<td>0.77</td>
<td>0.67</td>
<td>0.69</td>
</tr>
<tr>
<td>3</td>
<td>0.73</td>
<td>0.73</td>
<td>0.51</td>
<td>0.52</td>
</tr>
<tr>
<td>4</td>
<td>0.79</td>
<td>0.79</td>
<td>0.63</td>
<td>0.64</td>
</tr>
<tr>
<td>5</td>
<td>0.81</td>
<td>0.81</td>
<td>0.69</td>
<td>0.70</td>
</tr>
<tr>
<td>6</td>
<td>0.81</td>
<td>0.81</td>
<td>0.51</td>
<td>0.53</td>
</tr>
<tr>
<td>7</td>
<td>0.78</td>
<td>0.78</td>
<td>0.56</td>
<td>0.57</td>
</tr>
<tr>
<td>8</td>
<td>0.75</td>
<td>0.75</td>
<td>0.66</td>
<td>0.66</td>
</tr>
</tbody>
</table>
The comparison of the CRS scores with the VRS scores from the DEA models show that the conclusion can be made that a significant portion of the bank branches are operating under constant return to scale (CRS), since the scale efficiency for the groups range from 0.98 to 1.0 as shown on Table 5.6. This finding is consistent with the other researchers’ work [SHER85] [PARK87] [ORAL90] [SHER95] [SCHA97] [TOCH06]. Thus, only the CRS efficiency score was used in the analysis going forward.

Table 5.6   Model #1: Summary of CRS and VRS Average Efficiency Scores and Scale Efficiency

<table>
<thead>
<tr>
<th>BY SIZE</th>
<th>VRS</th>
<th>CRS</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Efficiency Score (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small</td>
<td>0.76</td>
<td>0.76</td>
<td>1.00</td>
</tr>
<tr>
<td>Medium-Small</td>
<td>0.62</td>
<td>0.61</td>
<td>0.99</td>
</tr>
<tr>
<td>Medium-Large</td>
<td>0.79</td>
<td>0.77</td>
<td>0.98</td>
</tr>
<tr>
<td>Large</td>
<td>0.94</td>
<td>0.94</td>
<td>1.00</td>
</tr>
<tr>
<td>Grand Average</td>
<td>0.73</td>
<td>0.72</td>
<td>0.99</td>
</tr>
</tbody>
</table>

When DEA results from the BCM’s recommended FTE count was compared to the DEA results from the actual paid FTE count, the average CRS efficiency scores were 71.8% and 73.4%, respectively. These results suggest that the bank branches in this study are actually in compliance with the BCM and perform closely to corporate management’s recommendations.

DEA has been used in many studies to evaluate performance based on resource allocations and was proven to be effective [HAAG95] [ROUA03] [TOCH06]. In this chapter, the proposed DEA model results were compared to the performance ratios currently used by the Bank (Section 4.3.4) to reveal any relationship between them. However, the two performance ratios used by the Bank were shown to have a significant weakness as they both had a strong positive correlation to the branch size, leading to a naturally lower performance efficiency score for smaller branches. Thus, when the performance ratios were compared to the DEA results, the result suggested no significant correlation between them. This is not unexpected, since no single ratio can appropriately represent the complex production process that banking has.
CHAPTER 6:

DEA MODEL #2 FORMULATION AND RESULTS:
EVALUATING BCM’S ACCURACY

This chapter provides an overview of the DEA model proposed to evaluate the accuracy of the staff allocating model of the Bank under study in meeting the desired benchmarks set by management. The BCM has a benchmark of meeting 85% of all transactions under either 5 or 10 minutes to reflect on customer satisfaction by promoting prompt services and reduced wait times while increasing face time between the customer service representatives and customers. In this chapter, DEA was employed to develop an evaluation system to validate or deny BCM’s accuracy in meeting the desired benchmarks set by management.

This section discusses the concepts and definitions of the proposed DEA model, input variables, output variables and non-controllable variables. Furthermore, a summary of the results of the DEA analysis is provided with information including CRS scores as well as comparisons with the Bank’s benchmarks.

6.1 Data Employed

The Bank under study provided detailed transactional data for 24 branches for a month of either January, 2011 or May, 2011. Since the transaction volume over the year for a bank branch does not experience any significant change throughout the year, two different month data were used indifferently. After removing large commercial branches, this model employed a dataset of all accounts of transactions over a one month period for 20 different branches. The branch data was further broken down to an hourly average of transaction data for each branch, increasing the size of the sample DMUs to 185.
6.2 Model #2 Formulation: Evaluating BCM’s Accuracy

The goal of this model was to evaluate the accuracy of the BCM in meeting the Bank’s desired benchmarks as well as to validate DEA’s ability to measure the efficiency of the BCM’s performance in comparison to the Bank’s desired benchmarks (internal metrics presented in Section 4.3.4). According to the Bank’s desired benchmark, this model compared DMUs with respect to their ability to have met a higher percentage of transactions under either 5 or 10 minutes.

The inputs of the DEA model consisted of BCM’s recommended FTE levels and the number of transactions over 5 or 10 minutes (according to the corresponding benchmark) over a one month period and the output variables of the model consisted of the total number of transactions over the one month period and the number of transactions under 5 or 10 minutes (according to the corresponding benchmark) for the same period. Desired serve time was the only non-controllable variable used in this model with the reduced number of DMUs. Figure 6.1 displays the input and output variables of the DEA model. The main objective of this model is at a given total volume of transactions, to reduce the number of resources required as well as the number of transactions over desired transaction time while maximizing the number of transactions under the desired transaction time.

![Figure 6.1 Model #2: List of Inputs, Outputs and Non-controllable variables for Evaluating Accuracy of BCM](image)

With 2 inputs and 1 output, a sufficient number of DMUs required for this study is minimum 9 DMUs\(^3\). Although, the group of DMUs for this study consisted of 20 branches, because of the non-controllable input these 20 branches would be segregated into 5 different desired

\[^3\ n \geq max\{m \times s,3(m + s)\} \rightarrow n \geq max\{2 \times 1,3(2 + 1)\} \rightarrow n \geq max\{2,9\} \rightarrow n \geq 9\]
serve time categories when compared, limiting the number of units for each comparison. Thus a two part analysis was conducted in this chapter, evaluating each branch as a DMU and evaluating each hour of the branch as a DMU, increasing the number of units to 185.

### 6.3 Empirical Findings

As concluded from chapter 5, the Bank in this study was performing at a constant-returns-to-scale model and thus only the CRS input oriented DEA model was employed to perform the following analyses.

Figure 6.2 shows the distribution of average total number of transactions per day by branch over the week. Average transactions per day were 271 with a standard deviation of 76, and as demonstrated by the distribution, total transactions per day were quite similar throughout the weekdays.

**Figure 6.2 Distribution of Average Total Transactions per Branch by Day**

<table>
<thead>
<tr>
<th>Day</th>
<th>Mon</th>
<th>Tues</th>
<th>Wed</th>
<th>Thurs</th>
<th>Fri</th>
<th>Sat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg</td>
<td>250</td>
<td>260</td>
<td>240</td>
<td>255</td>
<td>300</td>
<td>150</td>
</tr>
<tr>
<td>Std</td>
<td>30</td>
<td>35</td>
<td>25</td>
<td>30</td>
<td>50</td>
<td>20</td>
</tr>
</tbody>
</table>
Figure 6.3 shows the distribution of the average number of transactions by hour over the day. The average transactions by the hour were 32 with a standard deviation of 22 (69%), indicating a high variance in transaction volumes between different branches. As demonstrated on the distribution plot, peak hours consist of 10am to 4pm with significantly reduced transactions during mornings and evenings. Compared to the distribution by day, the distribution by hours showed significant variance throughout the day and thus was considered in the analyses to account for the variance between the hours, by considering each hour by branch as a DMU.

Therefore, a two-part analysis was performed on the data for this model. In the first part, a CRS input oriented DEA model was employed to evaluate the efficiency of the sample considering every bank branch as a DMU. In the second part, a CRS input oriented model was used to evaluate the efficiency considering every bank branch by hour as a DMU, increasing the number of DMUs to 185.
6.3.1 Model #2: Branches as DMUs

For the first run, each branch was used as a single DMU. A CRS input oriented model was used and 7 units were found to be CRS efficient (efficiency = 1). The average CRS efficiency score was 0.78 with a standard deviation of 0.21, as summarized in Table 6.1. Figure 6.4 displays the distribution of the CRS efficiency score and the distribution are skewed to the right with 40% of DMUs with efficiency scores above 0.9. High percentage of efficient branches is due to the result of small sample size. Many of the efficient branches are self-identifiers, not being able to be compared to enough number of peer branches to be considered inefficient. This demonstrates one of DEA’s major limitations handling small sample size as suspected. Therefore the next analysis was conducted with each hour of each branch considered as a DMU, increasing the sample size to 185.

Table 6.1 Model #2: CRS DEA Result for All Branches

<table>
<thead>
<tr>
<th>CRS Result</th>
<th>Branch as DMU</th>
<th>Branch by Hour as DMU</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of DMUs</td>
<td>20</td>
<td>185</td>
</tr>
<tr>
<td>No. of efficient DMUs</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>Average Efficiency Score</td>
<td>0.78</td>
<td>0.65</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.21</td>
<td>0.20</td>
</tr>
<tr>
<td>Maximum</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.38</td>
<td>0.31</td>
</tr>
</tbody>
</table>

Figure 6.4 Model #2: Distribution of CRS DEA Efficiency Score – Branch as DMU
6.3.2 Model #2: Branch by Hour as DMUs

In the second run, branch by hour was used as the DMU. For example, branch #1 would now have 8 DMUs for 8 working hours a day. A CRS input oriented model was used and 7 units were found to be CRS efficient (efficiency = 1). The average CRS efficiency score was 0.65 with a standard deviation of 0.20, as summarized in Table 6.1. Figure 6.5 shows the distribution of CRS DEA efficiency scores, which ranged from 0.31 to 1.00, with a varying distribution of DMUs across the range of efficiency scores.

Figure 6.5 Model #2: Distribution of CRS Efficiency Score = Branch by Hour as DMU

Compared to the first run (section 6.3.1) that considered each branch as a DMU, this run (each hour by branch as a DMU) shows much more comprehensive results and a varying degree of efficiency scores. Only about 5% of the units are efficient and DEA was able to identify inefficient branches and efficient branches with efficiency scores ranging from 30% to 100%.

A shortcoming of this run is that the input variable FTE at the branch level was averaged by the week. This model can be improved with hourly FTE data to more accurately depict the relationships between the inputs and the outputs on hourly needs.
6.4 Comparison with the Bank’s internal metrics

For the DEA efficiency score to be acceptable by the management, the estimated scores should be consistent (in some way and to some extent as the Bank’s system cannot be grossly out of reality) with the current measurements used by the Bank under study. Statistical analyses were conducted here to examine if there are any significant relationships between the obtained DEA efficiency scores and the fraction of the transactions under the benchmark ratio as introduced in Section 4.3.4.

The distribution of transactions under the benchmark is displayed in Figure 6.6 and it can be seen that the data is completely skewed to the right of the distribution, only ranging from 0.74 to 0.99 with an average of 0.89.

![Figure 6.6 Distribution of % Transaction under 5 or 10 minutes (according to benchmark)](image)

6.4.1 Branch by Hour as DMUs

In this analysis, the DEA results, where every branch by the hour was considered as a DMU, was used to compare against the Bank’s benchmark ratio (Eqn. 4.5). Figure 6.8 plots the CRS DEA efficiency score against the percentage of transactions under the benchmark (5 or 10 minutes). When linear regression was performed, the correlation coefficient (r) was 0.70 indicating a significantly high positive correlation between the DEA efficiency score and the
Bank’s internal metrics. This validates the proposed DEA model and results indicating that DEA is, in fact, a suitable tool to evaluate the Bank’s staff allocation model with respect to the Bank’s desired benchmark against customer satisfaction.

In summary, the correlation indicates a positive relationship between the CRS DEA efficiency score of the proposed model and the Bank’s benchmark ratio, the portion of bank transactions under the benchmark. Strong correlation can be seen from the branch level data as the correlation coefficient value is close to 1 and thus the proposed DEA model is viable in effectively measuring the branches’ efficiency according to the Bank’s desired benchmark.

Figure 6.7 CRS DEA Efficiency score vs. % of Bank Transactions under Benchmark: Branch by the Hour as DMU
6.5 Chapter Summary

In this chapter, a DEA model was proposed to evaluate the efficiency of branch operations meeting the desired service time benchmarks. Transaction by transaction data for a month provided by the Bank was used to model a CRS non-controllable variable included DEA model. After examining the distribution of average total transactions per day and distribution of average total transactions per hour, it was found that the hourly transactional volume indicated a significantly high variance that should be accounted for in the analysis. Thus, a two part analysis was conducted using branch as a DMU and branch by hour (this is the value when the transaction times are averaged on the hour) as a DMU.

CRS DEA model results revealed average efficiency scores of 78% and 65% for the DEA model built upon branch as a DMU and branch by hour as a DMU, respectively. Average efficiency scores were much higher when the branch was evaluated as a single DMU, because of the small sample size and large percentage of efficient branches being self-identifiers. One of the major shortcomings of DEA is its inability to evaluate small sample size and when each hour was segregated to be accounted as a DMU, the result was much more comprehensive with varying degree of efficiency scores across the distribution. However, the lower average efficiency scores for hourly FTE data indicated that the BCM still has improvement possibilities when allocating staff. Overall, the results support the BCM’s effectiveness in meeting the desired service time benchmarks.

The CRS DEA model result were then compared to the Bank’s desired service time benchmark ratio values (Section 4.3.4 – Equation 4.5) and showed a strong positive correlation between the DEA efficiency scores and the Bank’s benchmark ratio scores. This validates the proposed DEA model and results, and suggests that DEA is, in fact, a suitable tool to evaluate the Bank’s staff allocation model’s efficacy with respect to the Bank’s desired benchmarks.
CHAPTER 7:

CONCLUSIONS AND FINDINGS

This chapter concludes the research presented in this thesis by summarizing the discovery and contribution by this research for the Bank under study.

7.1 Key Analytic Contributions to the Bank’s Management Process

This thesis provides a summary of DEA and its application to a major Canadian bank’s branch network. It also compared DEA results to the Bank’s internal metrics to validate DEA’s ability to evaluate its bank branches’ efficiencies. The DEA model results not only evaluated the branch network efficiency but also identified areas for improvement and suggested areas for further investigation for the Bank. This thesis provided the Bank a practical methodology to evaluate their current model and can be used for future staff allocation system’s considerations.

The DEA results provide the efficiency scores in the context of staffing only of each branch in the Bank’s network. These scores captured how efficient or inefficient a branch is when compared to other branches. The reference set and targets provided by DEA suggests to management the type and amount of inputs and outputs changes are needed to improve each branch’s performance.

Moreover, the factors affecting branch performance may be found by analyzing the differences between efficient and inefficient branches. In-depth observations of the efficient branches that appear frequently and significantly in peer groups for the inefficient branches can provide insights into efficient operations can be conducted. In addition, other environmental factors such as geographic regions, branch size and other model levers used in
BCM have shown indications to characteristic advantage between groups of branches, which can be used to calibrate the staff allocation model to be a better fit. The comparison of DEA and the Bank’s internal metrics provided an overview of DEA’s ability to measure bank branch efficiencies. The most important contribution of this thesis is the proposed model in evaluating the accuracy of the Bank’s staffing allocation model to meet the desired customer satisfaction benchmark. Performance analysis is very important in any industry as it can be seen from the amount of academic research dedicated to the field. However, there are not many studies done from the perspective of customer satisfaction and comparisons of DEA results to the Bank’s ratios and benchmarks for validity.

Overall, the DEA results and the analysis can be used to estimate the potential savings from the improved performance. This research shows that the bank branches examined have a potential for improvement and detailed analysis combined with field study could achieve these improvements, hence accrue cost savings.

### 7.2 Findings Summary and Conclusions

This thesis developed DEA models in which the staffing allocation performance of the Bank’s branch network under study was evaluated. Productivity and efficiency measurement oriented DEA models were developed to evaluate the bank branch staffing allocation strategy by using different types of DEA models including non-controllable - constant returns to scale (CRS) and non-controllable - variable returns to scale (VRS). Two main DEA models were developed, (1) to evaluate the overall efficiency of the BCM and the branch network from strictly a staffing point of view and (2) to evaluate the accuracy of the BCM with respect to the Bank’s benchmarks in achieving the desired customer satisfaction experience.

An overview of the Bank under study and the data were presented in detail in chapter 4. The branches were classified into four major branch size groups: ‘small’, ‘medium-small’, ‘medium-large’ and ‘large’ branches, based on the number of FTEs, average weekly total number of transactions and average weekly business transactions. The Bank’s performance
ratios and benchmark ratios were reviewed in detail to understand their effectiveness in measuring their branches’ performance. The performance measuring ratios were found to be not adequate for the purpose as both ratios showed a significantly high correlation to the branch size, leading to a naturally lower efficiency score for smaller branches. Of course, this is one of the serious problems with single ratios used in this context.

The DEA results included overall and individual branch efficiency scores, which were then used to provide detailed managerial analysis. Overall, the comparison of CRS and VRS results showed that the branches under study were operating at constant returns to scale. Therefore, only the CRS results were used in chapter 6. In chapter 5, the DEA result showed that 15% of the Bank’s branch network was efficient (efficiency = 1) and the average efficiency score was 73%. This indicated BCM’s overall effectiveness in allocating CSR staff across their national branch network however there is still significant potential for improvement as DEA was able to identify well performing branches as well as inefficient branches with efficiency scores ranging from 18% to the fully efficient, 100%. The DEA results from chapter 5 were then compared against the Bank’s performance ratios. The comparison showed insignificant correlation, supporting the weaknesses in traditional ratio analyses for the use in measuring performance efficiency in the banking industry.

In chapter 6, the second DEA model proposed to evaluate the accuracy of the BCM’s recommendation meeting the Bank’s desired service time benchmark, showed DEA result of average efficiency score of 65% indicating BCM’s effectiveness yet much room for growth. DEA results were then compared against the Bank’s customer satisfaction benchmarks and this comparison indicated a strong correlation between the proposed DEA model and the Bank’s benchmark ratio, validating the use of DEA for evaluating branch efficiency in respect to the Bank’s desired customer satisfaction goals.

This thesis also provided a guideline for future performance analyses and a method for comparisons to DEA, for other banks as well as other industries. Banks are highly regulated in Canada and the large Canadian banks naturally adopt similar production technology and
operating methodology. Similar approaches could be taken by other banks in order to evaluate their own staffing methodologies and discover areas for improvement.

In summary, DEA is a very useful analytical tool for management in all kinds of decision making processes. In this study, DEA models were proposed to evaluate a major Canadian bank’s staff allocating model from the context of meeting their desired customer satisfaction benchmarks. Moreover, potential management use of DEA results were presented as each branch efficiency score and target provides insights into improving branch performance. Overall, this thesis provided valuable insights for management, regarding their current model and in directing future operational improvements.
CHAPTER 8:

RECOMMENDATIONS AND FUTURE WORK

This chapter provides recommendations for the Bank under study and possible areas of future work.

8.1 Recommendations

The performance measurement ratios used by the Bank were found to be not adequate for the purpose, as it has shown weakness in evaluating their branch network with its positive correlation to the branch size. This study therefore recommends application of DEA in efficiency measurement of the CSR allocation model, as DEA has widely been studied and explored as a performance measurement tool in the banking industry and has showed considerable success.

From the detailed analysis by branch size group and geographic region, DEA results identified relatively inefficient branch groups such as ‘Medium-Small’ branches and in region 3. These identified groups of branches should be further examined by the Bank to reveal potential improvements in CSR staff allocation.

Overall, DEA efficiency scores revealed a high percentage of efficient branches and a high average efficiency score of the national branch network supporting that the BCM is effective in allocating CSR staff across the Bank’s branch network. Furthermore, DEA analysis done on transaction-by-transaction data revealed a high efficiency average score in meeting the Bank’s desired service time benchmark and once again, supporting BCM’s accuracy in conforming to management’s desired inputs. However, DEA analysis done on hourly FTE data revealed a lower average efficiency score indicating that the BCM has room to improve in its guidance for branch operations to reach a maximum efficiency by hour.
As validated from this research, the proposed DEA model is recommended to be used by the Bank’s management to identify efficient and inefficient branches in allocating CSR staff with respect to meeting the Bank’s desired service time benchmark. This is a unique finding as not many studies have taken the perspective of customer satisfaction and furthermore, validated the proposed model’s viability against a bank’s actual desired benchmarks. With increasing understanding of DEA and its effectiveness in efficiency analysis, there are more industry friendly commercial software available for management’s use. The proposed DEA model can be easily utilized by the Bank’s management by employing commercially available DEA based software, to examine inputs and outputs changes needed to optimize each branch’s operation.

8.2 Future Work

Further examination and statistical analysis of the DEA results provided in this research could potentially reveal patterns for more effective branch operations such as the best staff mix between part time and full time staff, best team mix (number of CSR teams) and much more. Also, a limited sample size when evaluating the accuracy of BCM (Model #2) could be eliminated by obtaining more branch breakdown data to produce results reflecting the national branch network as well as hourly staff allocation efficiency. The proposed models should be extended in the future not only to evaluate the high-level staff allocation model but the branch manager level staff scheduling model to closely evaluate the branches’ efficiency and identify more potential savings and improvement upon operations.
REFERENCES


### Glossary

<table>
<thead>
<tr>
<th>Term</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Allocative Efficiency</td>
<td>Measure of the ability of a unit to use inputs in the most optimal proportions given a set of prices.</td>
</tr>
<tr>
<td>Bank’s Current Staff</td>
<td>A model that captures customer service staff allocation of a bank branch in terms of inputs needed for the branch to operate and outputs produced from its operations.</td>
</tr>
<tr>
<td>allocation Model (BCM)</td>
<td>DAE model which assumes a variable returns to scale relationship between inputs and outputs.</td>
</tr>
<tr>
<td>VRS or VRS Model</td>
<td>DEA model which assumes a variable returns to scale relationship between inputs and outputs.</td>
</tr>
<tr>
<td>BM</td>
<td>Branch Manager</td>
</tr>
<tr>
<td>BCM</td>
<td>See Bank’s Current staff allocating Model</td>
</tr>
<tr>
<td>Categorical Variable</td>
<td>Variable that assumes a predefined set of discrete values.</td>
</tr>
<tr>
<td>CRS Model</td>
<td>DEA model which assumes a constant returns to scale relationship.</td>
</tr>
<tr>
<td>Correlation</td>
<td>A measure of the strength of the relationship between two Coefficient variables. The value lies between +1 and -1.</td>
</tr>
<tr>
<td>CSR</td>
<td>Customer Service Representative (Tellers)</td>
</tr>
<tr>
<td>CSR:Expert</td>
<td>CSR Expert: Sub team of the CSR and is responsible for complex transactions such as foreign exchange.</td>
</tr>
<tr>
<td>CT</td>
<td>Central Teller: Sub team of the CSR and is responsible for business transactions</td>
</tr>
<tr>
<td>DEA</td>
<td>Data Envelopment Analysis: Non-parametric, fractional linear programming approach, which calculates relative efficiencies of Decision - Making Units (DMUs) and requires no prior specification of the functional form of the frontier.</td>
</tr>
<tr>
<td>DFA</td>
<td>Distribution Free Approach</td>
</tr>
<tr>
<td>DMU</td>
<td>Decision Making Unit: A term used to describe a unit being analyzed in DEA</td>
</tr>
<tr>
<td>Econometric Approach</td>
<td>A parametric approach for measuring efficiency, which requires a priori specification of the functional form.</td>
</tr>
<tr>
<td>EFA</td>
<td>Econometric Frontier Approach.</td>
</tr>
<tr>
<td>Term</td>
<td>Definition</td>
</tr>
<tr>
<td>-----------------------------</td>
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</tr>
<tr>
<td>Effectiveness</td>
<td>The ability of an organization to achieve its pre-set goals and objectives. A measure of “Doing the right things”.</td>
</tr>
<tr>
<td>Efficiency</td>
<td>The ability to attain the outputs with a minimum level of resources. A measure of doing things right.</td>
</tr>
<tr>
<td>Efficiency Gains</td>
<td>Changes in efficiency from one point in time to another</td>
</tr>
<tr>
<td>Efficient Frontier</td>
<td>Empirical frontier that represents “best performance” and consists of units in the data set, which is most efficient in transforming their inputs into outputs.</td>
</tr>
<tr>
<td>FDH</td>
<td>Free Disposal Hull.</td>
</tr>
<tr>
<td>FTE</td>
<td>Full-time-equivalent: Total number of full time positions required to complete the activities.</td>
</tr>
<tr>
<td>Input-Oriented Model</td>
<td>A DEA model whose objective is to minimize inputs while keeping the outputs constant.</td>
</tr>
<tr>
<td>Intermediation Approach</td>
<td>Approach in which a Financial Services Unit is viewed as a financial intermediary whose function is to invest deposits into profitable investments.</td>
</tr>
<tr>
<td>IO</td>
<td>Input – Oriented Model</td>
</tr>
<tr>
<td>IRS</td>
<td>Increasing Returns to Scale. A measure where a proportionate increase in inputs result in a more than proportionate increase in outputs.</td>
</tr>
<tr>
<td>MPSS</td>
<td>Most productive scale size. The point on the efficient frontier at which maximum average productivity is achieved for a given input/output mix.</td>
</tr>
<tr>
<td>Non-Discretionary Variable</td>
<td>A variable over which the management does not have control and therefore, cannot alter its level of use or production</td>
</tr>
<tr>
<td>Non-Controllable Variable</td>
<td></td>
</tr>
<tr>
<td>Output-Oriented Model</td>
<td>A DEA model where the objective is to maximize outputs while keeping the inputs constant.</td>
</tr>
<tr>
<td>Overall Efficiency</td>
<td>Efficiency measured as the product of technical and allocative efficiency.</td>
</tr>
<tr>
<td>Peer Group</td>
<td>Set of efficient units to which the inefficient units are compared.</td>
</tr>
<tr>
<td><strong>Production Approach</strong></td>
<td>Process in which inputs are transformed into outputs by a production unit.</td>
</tr>
<tr>
<td>--------------------------------</td>
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</tr>
<tr>
<td><strong>Production Function</strong></td>
<td>Function in which outputs are defined as functions of inputs.</td>
</tr>
<tr>
<td><strong>Productivity</strong></td>
<td>Defined as a ratio of outputs to inputs.</td>
</tr>
<tr>
<td><strong>Relative Efficiency</strong></td>
<td>A measure of actual performance of a production unit relative to best-observed performance of other similar units.</td>
</tr>
<tr>
<td><strong>Scale Efficiency</strong></td>
<td>Efficiency that indicates whether the unit is operating at its optimal size</td>
</tr>
<tr>
<td><strong>SFA</strong></td>
<td>Stochastic Frontier Approach.</td>
</tr>
<tr>
<td><strong>Slack Variable</strong></td>
<td>Represents the under-production of outputs or over-utilization of inputs in the DEA evaluation.</td>
</tr>
<tr>
<td><strong>Target</strong></td>
<td>The value of the inputs and outputs, which would result in an inefficient unit becoming efficient.</td>
</tr>
<tr>
<td><strong>Technical Efficiency</strong></td>
<td>Efficiency of the production process in converting inputs into outputs.</td>
</tr>
<tr>
<td><strong>TFA</strong></td>
<td>Thick Frontier Approach.</td>
</tr>
<tr>
<td><strong>Theoretical Frontier</strong></td>
<td>Frontier of best possible production.</td>
</tr>
<tr>
<td><strong>VRS</strong></td>
<td>Variable returns-to-scale. A measure where a proportionate increase in inputs could result in a proportionate increase or decrease in outputs.</td>
</tr>
<tr>
<td><strong>Weights/Multipliers</strong></td>
<td>Coefficients applied to inputs and outputs.</td>
</tr>
</tbody>
</table>