DETERMINING EFFICIENCY OF METRO OPERATIONS

Vasita Suriyamart
Department of Industrial Engineering, Faculty of Engineering, Mahidol University, Nakhon Pathom 73170 Thailand, E-mail: c.kanyarose@gmail.com

Jirapan Liangrokapart
Department of Industrial Engineering, Faculty of Engineering, Mahidol University, Nakhon Pathom 73170 Thailand, E-mail: jirapan.lia@mahidol.ac.th

ABSTRACT

At present, the rail-based mass rapid transit systems or metros in Thailand are composed of The Bangkok Mass Transit System(BTS), and the Mass Rapid Transit(MRT). Each system is operated by a different company under different terms of reference. There is no clear evidence to compare the efficiency of each system in consuming input resources to produce desired outputs. Previously, the performance between BTS and MRT have not been compared before. To make the benchmarking more efficiently, we need to have more metro operation that has a similar size to BTS and MRT. In this case, the metro operation from the NOVA member groups has been compared in this study. Hence, this research is to calculate the efficiency score for each system as well as to suggest ways for improvement for the inefficient systems. The Data Envelopment Analysis (DEA) model has been applied in this research to calculate the technical efficiency, pure technical efficiency, and scale efficiency values as well as to identify slacks and rank rail-based mass rapid transit systems. The selected rail-based mass rapid transit will be analyzed. The metro that achieved the highest efficiency score is that the Montréal Metro. BTS in Thailand attained the rank of 5th, but MRT ranked 10th of 15 rail-based mass rapid transit systems, this indicated that MRT inefficiency and need to improve.

Keywords : DEA, efficiency, slacks, super-efficiency, Rail-Basde Mass Rapid Transit, technical efficiency, pure technical efficiency, scale efficiency

1. INTRODUCTION

With increasing traffic demand, coupled with the increasing number of vehicles on the road, the problems related to traffic congestion, road accidents, and environmental pollution have also increased significantly over the last few years in various urban centers around the world. One of the most accepted methods of improving traffic and environmental conditions in these cities has been to provide an efficient public transportation system so that private vehicle owners are encouraged to shift to the public transportation system.

In various countries metro systems have been developed, Governments need to create new dynamics in railway transport for raising the need of customers for metro travel demand and compete better than other transportation modes and the social benefits for their country. Every metro system requires infrastructure, train stations, and rolling stock. Thus, the efficiency of these capitals is vital to justify the investment.

Mass rapid transit is significant for the urbanization of cities, and the demand for public transit has increased rapidly in recent years. Mass rapid transit systems in the Bangkok Metropolitan Region are expected to see increased uptake of services.

A greater number of people both living near mass rapid transit lines and using extensions to the lines are the passengers. The rail-based mass rapid transit is a rail system that is used for transporting passengers in urban areas. It is known by various other names such as mass transit, subway, underground railway, or metro (Sathapongpakdee, 2017).

The rail-based mass rapid transit in Bangkok to reduce traffic congestion consists of three services which are the Skytrain, the MRT subway, and the Airport Link. The Bangkok Mass Transit System (BTS), or sky train, and the Mass Rapid Transit (MRT), which is the subway, are electric train systems in central Bangkok and the perimeter, whereas the electric train linking Suvarnabhumi Airport (Airport Link) is a special project to facilitate those traveling to and from Suvarnabhumi Airport.

However, if the rail-based mass rapid transit system performance not reached the expectation, it will affect to reduce the potential demand and also get complaints and distrust from passengers. Thus, the operators of public transportation face not only the challenge to provide a cheap and efficient system from the passenger's standpoint but also to maximize operational efficiency as the means to secure the necessary profitability for maintaining the service.

Each rail-based mass rapid transit system is operated by different companies. Therefore, the performance measurement standard of each rail-based mass rapid transit operator is somewhat different. Moreover, the resources in each system are using not equally. Currently, rail-based mass rapid transit operators in Thailand are monopolistic, often with no source of performance comparisons with other systems. Each of the operators only seeks to achieve its specific measurable results based on their contracts. The rail-based mass rapid transit operations lack the measurement efficiency of their operation system, so they cannot improve the performance efficiently. Thus, this research comparing the efficiency performance of the rail-based mass rapid transit operators. Also, knowing the performance of each operator will help the low performing one to improve its performance and know how much it needs to improve output to reduce impacts or both.

The mission of rail-based mass rapid transit systems mostly aims to continuously develop their operations to manage their resources efficiently and provide reliable service. It is therefore imperative that the performance of the rail-based mass rapid transit system should be measured. Thus, the objective of this paper is to measure the efficiency of the BTS and MRT and compare the efficiency with rail-based mass rapid transit operated in other countries as well as offer recommendations for improvements of the inefficient rail-based mass rapid transit system.

However, information about the performance of rail-based mass rapid transit systems is very limited. A few sector associations apply tools to benchmark and carry out studies on benchmarking.

The scope of this paper is the operations performance of Bangkok rail-based mass rapid transit operators in Thailand. Selected members of the Nova group were used for benchmarking. This paper compares the operation performance of rail-based mass rapid transit systems at the international level and Thailand. However, the measuring system should be of a high standard and comparable among operators (MRT, 2017).

This study identifies the efficiency of the rail-based mass rapid transit system and the contributing factors in achieving high performance in the operation process. Rail-based mass rapid transit operators can use the results to adjust their strategy to improve their performance and process efficiency. Policymakers that are planning for future rail-based mass rapid transit projects may benefit from the experiences in other countries to make better decisions on the investments in infrastructure and rolling stock needed.

The rest of this paper is organized as follows. Section 2 is the meaning of performance measurement and efficiency. Section 3 reviews the research of benchmarking methods and efficiency analysis with DEA models to the railway industry. Section 4 introduces the CCR-DEA, Efficiency is the ratio between output and input, this is a key performance parameter indicating if assets are properly used. Efficiency requires reducing the number of unnecessary resources used to produce a given output (Coelli et al., 2005).

To attain operational efficiency a company needs to minimize redundancy and waste while using the resources that contribute most to its success and utilizing the best of its workforce and business processes. Moreover, operational efficiency can be defined as the ratio between an output gained from the business and input to run a business operation. When improving operational efficiency, the output will be increasing.

In the competitive era, the performance of the railway system needs to be improved especially on the metro system. However, evaluate efficiency that can be used to benchmark but for the rail-based mass rapid transit in Bangkok does not have that (yet) for comparing the efficiency of the system each rail-based mass rapid transit system in Bangkok. There is crucial for understanding how rail-based mass rapid transit services are running, for improving performance and to ensure that measures are aligned to strategy or not and that the system is working effectively in monitoring, communicating, and driving performance.

2. RELATED WORK

Benchmarking is used for business development as well as for improving the efficiency of any industry and intended to compare products or services with the competition or with organizations that are recognized as leaders in their sector to find best practices and ways to grow. This implies that it doesn't answer how industry leaders themselves can improve. The main objective of benchmarking is to measure and compare the realized output of a product or service with the number of inputs (Hansen et al, 2013).

Various research methodologies have been employed by scholars to evaluate the efficiency of European member state railways. The methodologies were generally classified into various categories such as data envelopment analysis (DEA), Partial Factor Productivity (PFP), Total Factor Productivity (TFP), and stochastic frontier analysis (SFA) (Coelli et al, 1999; Oum et al, 1999). First, the PFP method, This method is adopted in some studies (e.g. Wiegmans, 2007, Hilmola, 2007) and so on. This method claims the detailed prices of inputs and outputs. And which measures the ratio of a public transport system's output to a single input. The advantage of this approach is that it is easy to implement and understand, but the PFP measures only process one input against one output, and as a result, multiple Key Performance Indicators (KPIs) would be produced without a single overall indicator for benchmarking.

Some studies were employed in the TFP methodology (Karlaftis and McCarthy, 1997). The TFP approach generates a single index based on the ratio of aggregate output and an aggregate input in quantities. However, Oum et al. (1999) have suggested that aggregation problems may occur when producing a single index from multiple inputs or outputs.

Other methodologies used in the literature are SFA (Gathon and Pestieau, 1995, Cantos and Maudos, 2001, Karlaftis and Tsamboulas, 2012). The SFA uses an econometric model to estimate a firm's productivity based on its service inputs. Traditional cost or production functions are typically used to estimate the frontier of a firm's productivity and thus to identify the relative efficiency amongst multiple firms in the dataset. The SFA methodology is data-demanding and ideally, panel data are required to control for the unobserved heterogeneity (Karlaftis and Tsamboulas, 2012).

One of the major strengths of DEA is its ability to handle multiple input and output cases. Unlike parametric techniques, DEA has no difficulty in accommodating the multi-output structure of the railway (Oum and Yu, 1994). This thesis uses DEA to establish relative efficiency scores. The important reason for choosing DEA is the fact that railways are a multi-product (i.e. volume of passenger and kilometers a train operated) industry. Therefore, DEA’s ability to take into account multiple inputs and outputs is the decisive consideration in choosing our methodology.

Table 1. The input and output variable used in the railway efficiency studies using the Data Envelopment Analysis (DEA) method.

Variable	**Author**												
Input	Oum and Yu (1994)	Coelli and Perelman (2000)	Cantos et al. (2002)	Driessen et al. (2006)	Growitsch and Wetzel (2007)	Graham (2008)	Jain et al. (2008)	Sampaio et al. (2008)	Wang et al. (2009)	Cantos et al. (2010)	Santos et al. (2010)	Tsai et al. (2014)	Total
Number of employees	√	√		√	√	√	√	√	√	√	√	√	12
Length of network		√	√	√	√	√	√		√	√	√	√	12
Numbers of stations	√								√				2
Operation time									√				1
Energy consumption	√												1
Numbers of vehicles	√					√	√	√		√	√	√	7
Output													
The rate of a single fare									√				1
Passenger-km	√	√			√					√			4
Train-km					√	√	√				√	√	5
Passenger journeys				√		√	√	√	√		√	√	7
Operating cost			√										1

As seen in Table 1, the selection of inputs and outputs for this paper follows the literature (Oum and Yu, 1994, Coelli and Perelman, 2000, Cantos et al., 2002, Driessen et al., 2006, Growitsch and Wetzel, 2007, Daniel, 2008, Jain et al., 2008, Wang et al., 2009, Cantos et al., 2010, Santos et al., 2010, Tsai et al., 2014), which has generally suggested using Number of employees, Length of the network, Number of the station, and the number of stations as the input variables for the railway system. Also, the output variables have suggested using the Number of passenger journeys, and train-km traveled as the efficiency measure. Both variables are based on 2019 annual data.

DEA is however very suitable for use in the rail sector, due to the highly regulated and quasi-monopolistic industry structure (Coelli and Perelman et al, 2000) and where the formal link between input and output is not clear in the first instance. An important advantage of DEA is that the results are based on a relative comparison and that DEA can work with index numbers, ensuring that no sensitive information is provided to others as often desired by companies (Caldas, 2013).

BCC-DEA, SBM, as well as the SuperSBM. Section 5 presents the study area, data, variables, and also presents the analysis of 15 rail-based mass rapid transit efficiency both in Thailand and the selected Nova members group. Conclusions are drawn in the final section.

3. PERFORMANCE MEASUREMENT AND EFFICIENCY

The Benchmarking group of the large metro systems from around the world is that the Community of Metros or it calls CoMET, it was the first establishment in 1994 which comprises 17 larges metros. Then in 1998, the Nova Group of Metros was formed after the success of CoMET. the administrator and facilitates the process is the Transport Strategy Centre (TSC), at Imperial College London, the Metro benchmarking groups have the same objectives to prioritize areas for improvement, to introduce a system of measures for the management, and to build measures to establish metro best practice. The groups are jointly owned and steered by all members. Currently, CoMET and Nova are comprised of 42 large and medium-sized metro systems in 39 cities around the world.

Performance measurement of public transport systems can be categorized into efficiency and effectiveness (Hensher and Daniels, 1995). effectiveness can either represent the relationship between input factors and services consumed or between services produced and services consumed. Efficiency represents the relationship between input factors and services produced.

Therefore, the study of whether outcomes of operations are in line with set objectives. This process can be illustrated by an input-process-output (IPO) model, as shown in Figure 1: the feedback loop, this represents the performance measurement process or system.

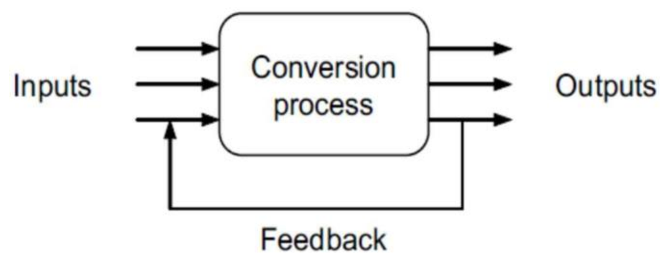

Figure 1, General input-process-output (IPO) model. ((Coelli et al., 2005)

An entity for describing the whole performance measurement process/system is commonly called a framework or model. Measuring can result in large savings and business safety if measuring leads to more proactive operations. Performance measurement is generally defined as the regular measurement of outcomes and results, which generates reliable data on the effectiveness and efficiency of programs.

Successful managers are concerned with customer satisfaction. (Liangrokapart, 2001) presents a method to compare the performance of organizational units within a supply chain using data envelopment analysis with measures of customer satisfaction as outputs and resources consumed by the units as input.

Nowadays, the objective of any firm is continuous performance. This is because it is only through performance that companies can experience development and make progress. Thus, assessing and measuring system performance is of significant importance, so that the companies are constantly seeking effective and efficient results.

DEA is a well-developed methodology for benchmarking the efficiency performance of multiple firms based on their service inputs and outputs in the transport sector. Especially for a firm's objective is to minimize service inputs for a given level of outputs. DEA is a proven non-parametric approach for benchmarking. It was initiated by Farrell (1957) and then developed by Charnes et al. (1978).

It is used for assessing the relative performance of a set of similar decision-making units (DMUs) with multiple inputs, and outputs to develop the best service profile which serves as the standard for efficient, low-cost service units, and is used as a target for the less efficient units (Coelli et al., 2005; Seiford, 1997; Banker et al., 1984; Charnes et al., 1978).

To determine whether a DMU is efficient or not from observed data is the equivalent of testing whether the DMU is on the frontier of the production possibility set (Cook et al., 2014; Molinero and Woracker, 1996). Efficiency measures the performance of a DMU by estimating its relative efficiency. Simple efficiency can be calculated using a ratio of output and input given in the following equation:

$$\text{Efficiency} = \frac{\text{Output}}{\text{Input}} \qquad (1)$$

However, in DEA, multiple inputs and outputs are linearly aggregated using weights. Therefore, the efficiency is measured as below:

$$\text{Efficiency} = \frac{\text{Weighted Sum of the outputs}}{\text{weighted sum of the inputs}} \qquad (2)$$

$$\text{Efficiency} = \frac{\sum V_r y_{ir}}{\sum u_j s_{ij}}$$

where u_j is the weight assigned to an input x_{ij} and v_r the weight assigned to output y_{ir} as given in Equation 2

4. METHODS

This research was analyzed based on the non-parametric approach of DEA. Using the DEA model for evaluating the efficiency of 9 DMUs. The traditional DEA model under the assumptions of constant and variable returns to scale is obtained by applying the DEA-CCR and DEA-BCC models respectively to get the technical efficiency, pure technical efficiency, and also scale efficiency of the 9 rail-based mass rapid transit.

The DEA-Solver-Learning Version (LV 8.0) software is used for the interpretation of DEA efficiency analysis. DEA-Solver was developed by Kaoru Tone. Interpretation of DEA efficiency analysis is shown in Figure 2.

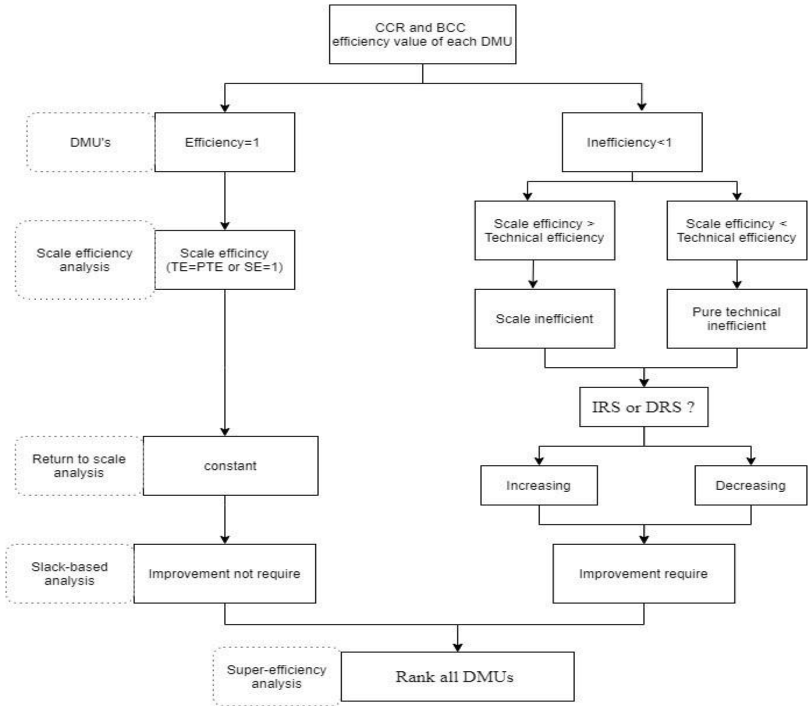

Figure 2. Interpretation of DEA efficiency analysis

In this section, at first, the models of Charnes, Cooper & Rhodes (CCR) and Banker, Charnes & Cooper (BCC) are described. The used notations for the model are summarized in Table 2

Table 2. Used notation.

Notation	Description
h_i	is relative efficiency value of DMU_i
X_{ij}	is the i input of DMU_i
Y_{ir}	is the r output of DMU_i
u_j	is the weight of j input
v_r	is the weight of r output
w_i	is scale factor of DMU_i

4.1. CCR model

This model proposed by Charnes, Cooper, and Rhodes (1978) for evaluating the efficiency of production units Also known as DMU which will consider the output of this model (input-oriented) under the assumption of Constant Return to Scale (CRS), which has a Linear programming model as follows;

Objective;

$$Max.\ h_i = \sum_{r=1}^{c} v_r y_{ir} \qquad (3)$$

Constraint;

$$\sum_{r=1}^{c} v_r y_{ir} \leq \sum_{j=1}^{N} u_j x_{ij} (i = 1,2, \dots, n) \qquad (4)$$

$$\sum_{j=1}^{N} u_j x_{ij} = 1 \qquad (5)$$

$$u_j, v_r \geq 0 \; ; j = 1,2, \dots, m; r = 1,2, \dots, s; i = 1,2, \dots, n$$

The purpose of the CCR model is to Making the highest performance of each decision-making unit valuable as the objective equation (3) and under constraint equation (4) and also need to set the weight of input and output variable, therefore, they must be positive value as equation (5).

4.2 BCC model

Banker, Charnes, and Cooper (1984) developed the new model is the BCC model to evaluate the performance Under the assumption of Variable return to scale (VRS) By Adding the change value of the factors in the DMUi into the objective function of the original CCR model, which has a linear programming model as follows;

Objective equation;

$$Max.\ h_i = w_i + \sum_{r=1}^{c} v_r y_{ir} \qquad (6)$$

Constraint;

$$w_i + \sum_{r=1}^{c} v_r y_{ir} \leq \sum_{j=1}^{N} u_j x_{ij} (i = 1,2, \dots, n) \qquad (7)$$

$$\sum_{j=1}^{N} u_j x_{ij} = 1 \qquad (8)$$

$$u_j, v_r \geq 0 \ when\ j = 1,2, \dots, m; r = 1,2, \dots, s$$

The purpose of the BCC model is to Making the highest performance of each decision-making unit valuable as the objective equation (6) and under constraint equation (7) and also need to set the weight of input and output variable, therefore, they must be positive value as equation (8).

4.3 Scale efficiency (SE)

We employed both CCR and BCC models on this thesis to find the Technical efficient (TE) and Pure technical efficient (PTE) respectively. Coelli, et al. (1998) proposed the concept About Calculating the efficiency value per scale (Scale efficiency; SE) as the equation (9) can be calculated from the different score form the CCR model and BCC model;

$$SE = \frac{CCR\ score}{BCC\ score} \qquad (9)$$

For the resulted of this equation if SE = l signifies a scale efficiency. On the contrary, if SE < 1 (or SE > 1) means that DMU is at the inefficient stage of decreasing or increasing returns to scale, which can be taken as a reference for modifying the productive scale by a policymaker

4.4 Returns to scale analysis

Returns to scale model are used to whether evaluate rail-based mass rapid transit is in a status of constant, increasing, or decreasing. The classification of RTS for an inefficient DMU can be estimated if the inefficient DMU can be projected onto the efficient frontier (Seiford & Zhu, 1999). Since all inefficient DMUs are not operating at the optimum scale efficiency, the main justification of calculating RTS is to classify the region of an inefficient DMU whether it is operating in IRS or DRS regions. The main aim of calculating the efficiency scores under CRS and VRS is to estimate the nature of returns to scale of the input-oriented DEA model. This thesis employs the three conditions proposed by Zhu and Shen (1995). These conditions depend on the values of the intensity factor λj corresponding to the efficiency scores of the CRS technology (Saranga, 2009) and the CCR model is employed to determine whether this DMU in the state at constant or decreasing or increasing returns to scale. The three conditions of returns to scale are presented as follows:

If $\sum_{j=1}^{N} \lambda_j x_{ij} = 1$, then it is assumed constant returns to scale (CRS)

If $\sum_{j=1}^{N} \lambda_j x_{ij} \geq 1$, then it is assumed decreasing returns to scale (DRS)

If $\sum_{j=1}^{N} \lambda_j x_{ij} \leq 1$, then it is assumed increasing returns to scale (IRS)

4.5 Slacks based measure (SBM)

Slacks based measure (SBM) is a non-radial model to solve the problem in the "additive model" developed by Charnes, Cooper, & Rhodes in 1978 for evaluating the efficiency of decision-making units (DMUs) has been well developed in different directions. The SBM model is an important branch of data envelopment analysis (DEA) and identifies all inefficiencies of the concerned DMU. This model can discriminate between efficient and inefficient Decision-Making Units. SBM model uses "slacks" to show excess input and output shortfalls into the evaluation.

Many models based on SBM have been built, such as SBM of super efficiency, and SBM of the worst-practice DEA. The motivation for the development of this model is the observation that while both the CRS and the BCC models calculate efficiency scores, neither is able to take into accounts the resulting amount of slack for inputs and outputs.

We represent the input-oriented models to introduce the additive model which employs slacks to detect all inefficiency resources.

Therefore, the purpose of this model is to minimize the input and output slacks, resulting in this fractional program, which is converted to a linear program before solving it. The performance score E_O of each DMU_O is found by solving the SBM model shown in the objective equation (8), This model proposed by Tone and Tsutsui (2001).

The model is described as follows. Consider there are n DMU_c: DMU_1, DMU_2, …, and DMU_n. Each DMU_j, (j = 1, 2, …, n) uses m inputs x_{ij} (i = 1, …, m) and generates s outputs y_{rj} (r = 1, …, s). and Under constraint equation (9), let the vector of non-negative slack associated with the output slacks be s_r^+ (r = 1, …, s). Under constraint equation (10), let the vector of non-negative slack associated with the input slacks be s_i^- (i = 1, …, m). Let the DMU_j to be evaluated on any trial be designated as DMU_O (0 = 1, 2, …, n), and λ is a non-negative vector of weights for the inputs and outputs.

Objective equation;

Min E $1-\frac{1}{N}$ … $\sum_{i=1}^{i}$ … i0

(8) $\quad_{O} \quad \overline{1+\frac{1}{c}\sum_{r=1}^{c}\frac{c^{+}_{r}}{y_{r0}}}$

Constraint;

$\sum_{j=1}^{N}\lambda_j x_{ij} + s^{-}_{i} = x_{i0}$ (9)

$\sum_{j=1}^{N}\lambda_j y_{rj} - s^{+}_{r} = y_{rO}$ (10)

$\sum_{j=1}^{N}\lambda_j = 1 \ when\ \lambda_j, s^{+}_{r}, s^{-}_{i} \geq 0$

The highest score a DMU is equal to 1, which is only achievable when all slacks are equal to zero. In the optimal solution of the model, if $E_0 = 1$ and $s^{+}_{r} = s^{-}_{i} = 0$, The DMU is called DEA efficient, if $E_0 < 1$ and $s^{+}_{r} \neq 0, s^{-}_{i} \neq 0$, the DMU is called DEA inefficient.

4.6 Super SBM DEA

SBM model fails to provide an efficiency measure, so a decision-maker cannot interpret the performance of the DMU. To address this issue, the DEA models that relax the condition for unit efficiency that calls The Super efficiency analysis or "super SBM" model in most DEA models, it was introduced by Tone and Tsutsui (2001) extended the super SBM (SupSBM) model, as a non-radial variant of the super efficiency approach of Andersen, Petersen (1993), which considers the slacks to determine and rank efficient DMU. It is appropriate for evaluating efficiencies when inputs and outputs may change non-proportionally.

For an SBM efficient DMU_O, Tone (2002) proposed the Super SBM model to identify its super efficiency, shown in the objective equation (11),

$$\delta = \frac{\frac{1}{N}\sum_{i=1}^{N}\frac{\bar{x}_i}{x_{i0}}}{\frac{1}{c}\sum_{r=1}^{c}\frac{\bar{y}_r}{y_{r0}}} \qquad (11)$$

$\bar{x}_i \geq \sum_{j=}^{n} \lambda_j x_{ij},$ i=1,…,m

$\bar{y}_r \leq \sum_{j=}^{n} \lambda_j y_{rj},$ r=1,…,s

$\lambda_j \geq 0,$ j=1,…,n

$\bar{x}_i \geq x_{iO},$ i=1,…,m

$\bar{y}_r \leq y_{r0},$ r=1,…,s

Assuming that there are 'n' DMUs producing the same set of outputs that consume the same set of inputs. associated with m inputs and s outputs. Let x_{ij} denote the i^{th} input of DMU_j and y_{rj} denote r^{th} output of DMU_j. Assume that all data are positive, i.e., $x_{ij}, y_{rj} > 0$ for all possible i=1,…,m; r=1,…,s; j=1,…,n.

5. EXPERIMENT RESULTS AND DISCUSSION

The data were collected from publicly available annual reports or the open-source from the operators' official websites in 2019. This paper attempted to collect data from more rail-based mass rapid transit system operators in Nova member groups, but most of the operators do not publicly release their operating data. The set of 15 rail-based mass rapid transit systems is the largest sample size this paper could achieve with consistent data without missing variables.

Boussofiane et al. (1991) determined that to get good discriminatory power out of the CCR and BCC models the minimum on the number of DMUs should be multiple of the number of input variables and output variables. For example, if there are 2 outputs and 4 inputs the minimum total number of DMUs should be 8 for some discriminatory power to exist in the model. Roll and Gollany (1989) mentioned that the execution of efficiency analysis could depend on multiple inputs and outputs but different items may affect its result; furthermore, a plethora of inputs and outputs will reduce the segmentation effect of DMUs. Table 3 shows DMUs are the 15 systems of rail-based mass rapid transit, whose inputs and outputs are as in Table 4, and the values of inputs and outputs are summarized in Table 5.

Table 3. DMUs of the data

$\boldsymbol{DMU_1}$	MRT
$\boldsymbol{DMU_2}$	BTS
$\boldsymbol{DMU_3}$	Istanbul Metro
$\boldsymbol{DMU_4}$	Kuala Lumpur RapidKL Rail
$\boldsymbol{DMU_5}$	Newcastle Tyne & Wear Metro
$\boldsymbol{DMU_6}$	Metropolitano de Lisboa
$\boldsymbol{DMU_7}$	Bangalore Namma Metro
$\boldsymbol{DMU_8}$	Sporveien Metro
$\boldsymbol{DMU_9}$	Dubai metro
$\boldsymbol{DMU_{10}}$	Rio de Janeiro Metro
$\boldsymbol{DMU_{11}}$	Vancouver SkyTrain
$\boldsymbol{DMU_{12}}$	Washington Metro
$\boldsymbol{DMU_{13}}$	Brussels Metro
$\boldsymbol{DMU_{14}}$	Metro de Barcelona
$\boldsymbol{DMU_{15}}$	Montréal Metro

Under a metro context, capital inputs include the trains, track, stations, and all other fixed infrastructure. The labor factor is work carried out by total staff. The output produced by metro operators can be either volume of passengers or kilometers operated. The output is referred to as the final output and indicates the effectiveness of a metro. (Schreyer, 2001, and Coelli et al., 2005).

The selection of inputs and outputs for this paper follows various literature three capital factors are considered, track (total length of a network used by trains operating in passenger service, also referred to as network length), fleet or vehicle (total number of cars), and the number of stations served. For labor, total operation staff is incorporated. Therefore, the output performance can be expressed in terms of travel volume and is defined as the product of the yearly number of passengers. Ridership and train kilometers produced by the fleet are additional output variables indicating the railway's performance.

Table 4. Inputs and outputs of DMUs

	Variables	**Notation**	**Definitions**
Inputs	Track	X_1	Total railway route length (km.)
	Vehicles	X_2	Total number of cars owned by operators (unit) \
	Station	X_3	The number of stations served
	Labour	X_4	Total operation staff
Outputs	Passenger journey	Y_1	The yearly number of passengers per Year (millions)
	Vehicle per kilometers Traveled	Y_2	The number of kilometers a train operated annually (millions)

Table 5. The values of inputs and outputs

DMUs	X_1	X_2	X_3	X_4	Y_1	Y_2
1	71	225	54	1114	137.26	3.888
2	53.9	316	48	3172	247.6	4.863
3	115.3	647	89	4565	495	6.615
4	156.7	954	116	1270	290.1	8.066
5	77.5	89	60	515	36.4	4.866
6	44.5	113	56	1424	173	2.552
7	42.3	150	40	1483	134.4	3.806
8	85	115	101	623	118	9.1
9	74.6	590	49	3724	200.075	9.7
10	58	294	41	2230	228	2
11	79.6	298	53	1700	160	4.114
12	188	1126	91	2331	182	10.1
13	39.9	66	59	1230	138.3	2.7
14	189	1300	166	3203	407	12.3
15	69.2	909	68	900	383.147	7.4

The DEA-CCR and DEA-BCC input-oriented models were conducted for measuring efficiency, returns to scale, slacks, and super efficiency of nine rail-based mass rapid transit systems. The model is that it involves solving a complex equation. It takes a lot of effort and time to estimate the efficiency of different decision-making units manually. Therefore, it is optimal to use statistical packages than manual calculations. The DEA efficiency value was evaluated using the DEA-Solver-Learning Version (LV 8.0) software.

Table 6. The result of Data Envelopment Analysis

DMU	DEA-CCR	DEA-BCC	SE	$\Sigma\lambda$	RTS
1	0.8497	0.9683	0.8775	0.27	Increasing
2	1	1	1	1	Constant
3	1	1	1	1	Constant
4	0.6822	0.6881	0.9914	1.04	Decreasing
5	0.8673	1	0.8673	0.33	Increasing
6	1	1	1	1	Constant
7	1	1	1	1	Constant
8	1	1	1	1	Constant
9	1	1	1	1	Constant
10	1	1	1	1	Constant
11	0.796	0.8218	0.9686	0.51	Increasing
12	0.8816	1	0.8816	1.12	Decreasing
13	1	1	1	1	Constant
14	0.676	1	0.676	1.06	Decreasing
15	1	1	1	1	Constant

As seen in Table 6, according to the result of the DEA-CCR model, it implied that six out of fifteen rail-based mass rapid transits were inefficient with score technical efficiency less than 1 or less than 100 percent. It denotes that they performed inappropriately or have not fully utilized their resources, otherwise it indicates that all inefficient rail-based mass rapid transits can handle more output. So, they need to expand their output to be able to achieve optimum utilization of their resources. For an example of Metro de Barcelona with a technical efficiency score of 67.6 percent, it means that they have less utilization of input or their resources by 32.4 percent. Thus, Metro de Barcelona needs to improve the utilization of its resources.

A result of the BCC model, 12 DMUs are found as efficient with relatively pure technical efficiency with a score equal to one. However, based on the results obtained with the CCR model, only nine units are efficient. The DEA-BCC yield found more metro are efficient than DEA-CCR.

The BCC model showed that MRT (0.9683), Kuala Lumpur RapidKL Rail (0.6881), and Vancouver SkyTrain (0.8218) are overall technical inefficient and pure technical inefficient. This evinces that these metros managerial inefficiency and these metros should redesign management practices for better usage of it is resources. Moreover, 12 metros are stated in purely technically efficient, it is implied that they utilize of its input as well as good in managerial practices.

According to the results obtained with the SE model as shown in Table 6, the result shows that 9 metros are scale efficiency with scores equal to 1 or achieving the scale efficiency. These 9 metros are considered to have operated at an optimal scale.

The SE model This evinces that 6 metros managerial inefficiency and these metros should redesign management practices for better usage of it is resources and need to extend their scale. Other 9 metros are considered to have operated at an optimal scale. the efficiency of 9 DMUs is more than one or achieving the scale efficiency

For the inefficient metros, there is still room to improve their efficiencies by determining their slacks of inputs and outputs under the SBM model as presented in Table 7.

Table 7. Value If Efficiency in inputs and oiutputs under SBM Model

DMU	X_1	X_2	X_3	X_4	Y_1	Y_2
1	40.9490	225	46.6019	621.4745	137.26	3.888
4	75.3929	628.6858	80.3954	806.3133	290.1	8.066
5	45.4516	61.4934	54.0073	333.1338	63.0975	4.866
11	42.16013	298	46.6183	617.6525	160	4.114
12	88.9393	359.2124	91	1761.0349	182	10.1
14	114.9583	858.2355	124.3374	1181.1017	407	12.3

In Table 7, we can see that all inefficient metros owe their problems to input slacks (input excesses) and some of the output slacks (output shortfalls). For instance, MRT has an excess in three inputs which are track kilometers, vehicles, and labours. Thus, to improve the efficiency of This DMU, all of its inputs should be decreased by 22.5, 94, and 28, respectively. In the case of Newcastle Tyne and Wear Metro, they have excess in all its inputs and some output shortfalls. Thus, to improve the efficiency of Newcastle Tyne and Wear Metro, all of its inputs should be decreased by 32, 27,6, and 181, respectively, while its outputs need to improve the efficiency of Newcastle Tyne and Wear Metro should be increased in Passenger journey traveled per year by 29.19.

Note that the slack of output shortfall of kilometers a train operated annually for all the inefficient metros is equal to zero as presented in the last row of Table 7. This result reflects that the inefficient metros are operating effectively under this output.

Table 8. A comparison of efficiency value and ranking in different analysis models

DMU	**DEA-CCR**		**DEA-BCC**		**DEA-SupSBM**	
	Score	**Rank**	**Score**	**Rank**	**Score**	**Rank**
1	0.8497	12	0.9683	13	0.749406	10
2	1	1	1	1	1.094714	5
3	1	1	1	1	1.033419	7
4	0.6822	14	0.6881	15	0.617021	14
5	0.8673	11	1	1	0.706098	11
6	1	1	1	1	1.080246	6
7	1	1	1	1	1.02384	8
8	1	1	1	1	1.650823	2
9	1	1	1	1	1.311741	3
10	1	1	1	1	1.003816	9
11	0.796	13	0.8218	14	0.693142	12
12	0.8816	10	1	1	0.636896	13
13	1	1	1	1	1.108656	4
14	0.676	15	1	1	0.596549	15
15	1	1	1	1	1.897719	1

The CCR and BCC models provide a method to classify rail-based mass rapid transit or metros into efficient and inefficient metros, but it is difficult to decide the relative ranking among efficient metros. While there are several metros represent score efficiency equal to one as in this paper, it is difficult to determine which metro is more efficient than other metros. To addresses this issue, super-efficiency DEA has been proposed to further distinguish among those DMUs sharing the same score of one and rank them.

As seen in Tables 8, the results of the comparison in a different model, the result that all units are efficient is not helpful for decision-makers and cannot be used for the ranking of units. In this case, one of the approaches used for ranking is the super-efficiency or SuperSBM model in which the evaluated units are removed from the set of DMUs and the evaluation is made over the updated frontier. So, in the SuperSBM approach, the result efficiency scores of inefficient units remain inefficient units as in the traditional DEA model. However, the efficiency scores of efficient units are higher than one. Hence, this approach also ranks among efficient units.

6. CONCLUSIONS

As reviewed in relation works, the advantage of DEA is its capability to generate efficient performance of processing multiple inputs and outputs for benchmarking. The main purpose of this paper is to measure the efficiency of the BTS and MRT and compare the efficiency with rail-based mass rapid transit operated in other countries, Then, offer recommendations for improvements of the inefficient rail-based mass rapid transit system. In this study, BTS and MRT systems in Thailand have been compared to other Rail-based mass rapid transit systems with other countries in the Nova members group, and some suggestions have been offered for the current system.

As a result of the input-oriented CCR model with the assumption of CRS, rail-based mass rapid transit systems with an average efficiency value of 0.91. BTS has scored higher than the average score with 1. But, MRT has the lowest efficiency value at 0.85.

According to the VRS assumption of the input-oriented BCC model, 12 of 15 Rail-based mass rapid transit systems have been founded as efficient after the analysis of the input-oriented BCC model. BTS has been found as having one of the efficient Rail-based mass rapid transit systems with its 1.00 efficiency score. But, MRT stills an inefficient system with its 0.96 efficiency score.

The scale efficiency score under VRS and CRS assumptions, the result indicated that nine systems are efficient because they achieved optimum size.We rank the DMUs using the SuperSBM model, whose result is not the same as the order found with the approach CCR-DEA and BCC-DEA model. The metro that achieved the highest efficiency score is that the Montréal Metro, which is ranked first with a SuperSBM score of 1.897719 this replied that this metro performed more efficiently than the other. The Montréal Metro achieved a higher passenger journey per year and kilometers a train operated per year output with a small number of resources.

The model used in this thesis is input orientated, therefore inefficiency means that those rail- based mass rapid transits have excess input at the level of its output. To achieve efficiency these rail-based mass rapid transits have to improve their input following the slack analysis as shown in Table 4.6 and reference sets and target values have been determined for inefficient Rail-based mass rapid transit systems.

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