**Master's Thesis of City Planning in Transportation Studies**

# Evaluating the Efficiency of Bus Operation Routes in Jakarta

자카르타의 버스 노선의 운행 효율성 평가

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# Abstract

The purpose of the thesis is to evaluate the efficiency of Jakarta's public bus system (Transjakarta) by comparing output and input of bus routes operation. The Stochastic Frontier Analysis (SFA) is conducted to examine this analysis. This paper also compares Translog and Cobb-Douglas functions to identify a robust production function. To develop an appropriate model, the data of 131 routes of the Jakarta public bus in 2020 were used. The passenger-kilometer is set as an output variable, and the vehicle-kilometer, bus capacity, and service area population are set as input variables. The results show that the Cobb-Douglas is preferable to the Translog production function. It also shows that, the number of seats, the vehicle-kilometer, and the service area population positively are correlated with the passenger-kilometer. The routes with small-size buses have shown higher average technical efficiencies than those with large-size buses. It means that size of buses can contribute to bus service efficiency. In addition, the results reveal that both the small-size and large-size bus routes have a minimum efficiency of around 0.2 and a maximum efficiency of approximately 0.9, indicating a significant efficiency disparity among bus routes. The lowest efficiency indicates that the service provision is greater than the demand. It denotes that the efficiency of some routes can be improved by reducing the vehicle-kilometer and the number of seats per bus.

**Keywords:** evaluation, efficiency, bus routes, Stochastic Frontier Analysis (SFA), production functions

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# Chapter 1. Introduction

## 1.1. Study Background

Indonesia is one of the developing countries and one of the world's most populous nations — having a population of 276,361,781 in 2021 and a growth rate of 1% (world's population). The population is dispersed among 33 provinces, starting from Sabang (Northeast Region) to Merauke (Eastern Province). About half of Indonesia's population resides on Java Island, which comprises just 7% of the country's total territory (Kompas.com).

As a capital city, Jakarta had 10.56 million people in 2020. As a metropolitan city, it attracts tourism (Jakarta Central Statistics Agency). Moreover, Jakarta is the third-largest metropolitan area in the world, after Tokyo and Delhi, with 29.8 million inhabitants. Consequently, the greater Jakarta (Jakarta, Bogor, Depok, Tangerang, and Bekasi) are being built as a megapolis city according to the government plan. Therefore, integrated transportation systems are necessary for Jakarta.

Due to the lack of public transport facilities to provide integrated mobility, private automobiles continue to dominate Jakarta's traffic, and the number of motorcyclists remains substantial. According to a forecast by Jakarta's Central Bureau of Statistics, the total number of automobiles on Indonesian roads expanded significantly to 20.22 million in 2020. Jakarta's Central Bureau reported that the increasing number in population results in an increase in the number of private vehicles. Hence, both the population and automobile ownership have been increasing in Jakarta.

In Jakarta, road construction has not equal to the growth of motorization in Jakarta. In 2019, Jakarta had 160,350 kilometers of highway, 57,696 kilometers of principal arterial road, 2,160 kilometers of primary collector, and arterial and collector secondary roads totaling 694,460 kilometers and 788,618 kilometers respectively (Jakarta's Central Bureau of Statistics). Due to the continual rise in the number of vehicles, slow road construction and poor road management

contribute to congestion. The insufficient width of the road to accommodate the number of vehicles is the major cause of the congestion. According to the 2019 World Economic Forum, Jakarta ranks eleventh in the category of most congested cities in the world. Subsequently, a traffic management system is necessary to mitigate the congestion.

A good traffic management system must accommodate public transportation with a substantial mode share that provides road users greater efficiency than a private vehicle. In response to this issue, official agencies in Jakarta are working toward the development of public transportation in Jakarta in order to alleviate the congestion in the city. Until 2021, a number of transportation facilities were built in Jakarta, including Mass Rapid Transit (MRT), Light Rail Transit (LRT), electric rail cars, and the Jakarta public bus – commonly known as Transjakarta.

Transjakarta reportedly commenced operations in February 2004 as the first bus rapid transit in Southeast Asia and South Asia. The expansion of Jakarta's service coverage was accomplished by Transjakarta in 2010 with the opening of routes 9 and 10. Therefore, Transjakarta began integrating with another operator in 2011 to provide feeder service coverage. In 2013, the public service facility expanded its use of e-ticketing to promote ticket unification between routes. There are a number of Transjakarta services, like the woman-only bus, Transjakarta cares, and a free service car for disabled people. In 2019, the service covered Jakarta's whole metropolitan area and consisted of 247 routes.

Until 2020, public attention has been sparked by the growing number of bus passengers as a result of the expansion of Transjakarta’s routes. Nevertheless, Transjakarta services must be accessible to the general public in terms of cost, service scope, and coverage area. One example is Transjakarta's collaboration with another operator to provide the fleet. Alternately, a partnership with a specific bank is to facilitate payments. Those are several strategies that could be implemented to enhance the transportation quality.

During the last eighteen years, Transjakarta has been operating, significant customer service enhancements have been found on each of its routes. However, there are a number of service-related issues, including passenger queues on particular routes, bus accidents, and sexual harassment.

Most of all, there is a difference in the overall performance of bus service between to routes. Some routes are attracting many passengers with relatively less number of vehicle-kilometer. Other routes are attracting less number of passengers while providing a high number of vehicle-kilometer.

## 1.2. Purpose of the research

The primary objective of this research is to determine the technical efficiency of Jakarta's metropolitan public bus services, namely Transjakarta. To evaluate the performance of public bus services, Stochastic Frontier Analysis (SFA)as a type of economic evaluation, will be applied. Data is obtained from the 2020 annual report of the Transjakarta public bus transportation authority. The efficiency measurement from the SFA is applied in two production functions, namely the Cobb-Douglas and the Translog production function. Those functions are used to evaluate the efficiency of bus routes.

## 1.3. Structure of Thesis

This thesis is divided into six chapters. The first chapter serves as an introduction to the topic. The second chapter discusses some theoretical background of the efficiency idea and measurement. In addition, it includes a summary of the Stochastic Frontier Analysis (SFA) in the scientific literature. Particular attention is paid to empirical studies that scrutinize how services are evaluated by using the SFA. The third chapter explicates the detailed concept of the stochastic production function. Consequently, it outlines the comparison between these two methods of calculating production functions (Cobb-Douglas and Translog). The data are provided in the fourth section. The fifth chapter presents the application results from the stochastic production function form. It shows evaluates the technical efficiency of the bus routes. The final chapter summarizes the results and outlines the suggestions for further studies.

# Chapter 2. The State of the Art

Firstly, this chapter explains relevant studies on the concept of efficiency. Secondly, it presents a Stochastic Frontier Analysis (SFA) as a technique for efficiency measurement. The final section summarizes previous research which used Stochastic Frontiers Analysis (SFA) in transportation.

## 2.1. The Efficiency Concept

Oxford English Dictionary (OED)'s first edition defines efficiency as "the quality of doing something well with no waste of time or money", while the OED's second definition is "ways of wasting less time and money or of saving time or money". Hence, the efficiency in this research is perceived in general.

In economic terms, "economically efficient" refers to a state in which every resource is used to best serve the interests of all parties while minimizing waste (conceptual.org). Resources that are wasted indicate inefficiency because we could have produced more output with the input we already had or achieved our desired outcomes with less input.

In most cases, efficiency is defined as the maximization of outputs relative to inputs. In other words, it is the capacity to do something efficiently and effectively. In the field of transportation efficiency, the term is used to measure how well transportation services meet customers.

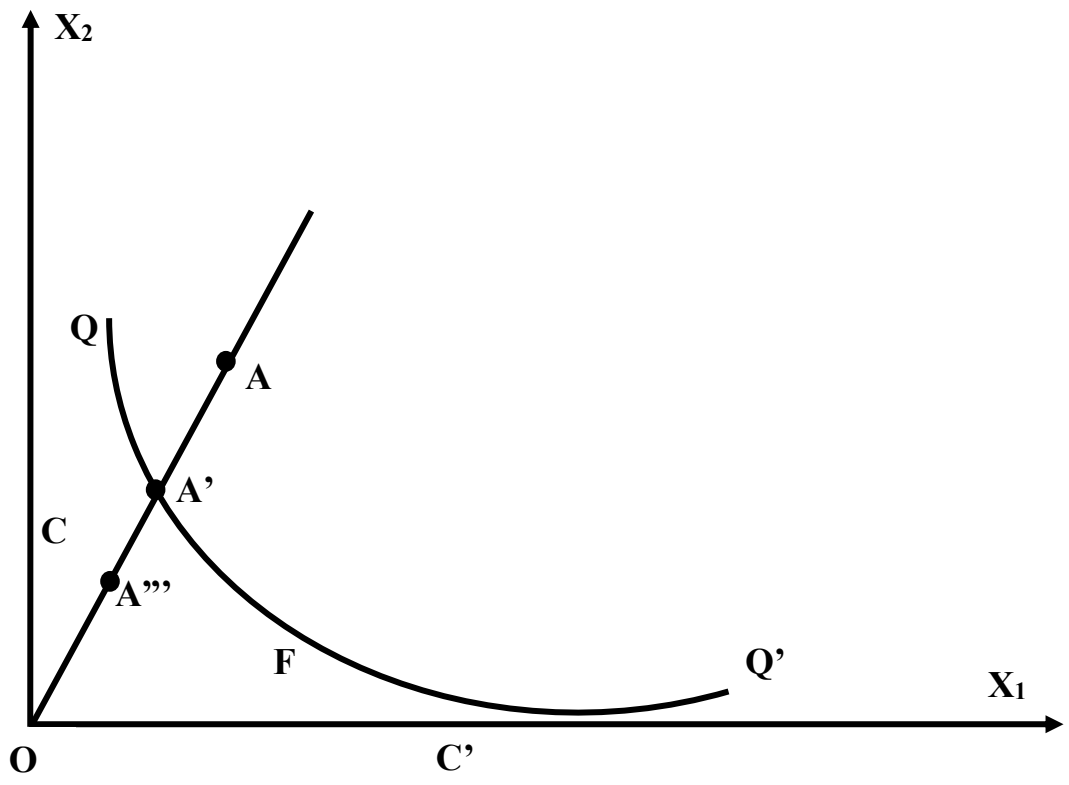
A number of researchers pioneered the idea of efficiency. As Koopmans (1951) states, "An attainable set of commodity flows [or attainable point in the commodity space] is called efficient if there is no other attainable set of commodity flows in which all flows are at least as large as the corresponding flows in the original set, while at least one is actually larger" (pp.460).

In contrast to Koopman (1951), who defines efficiency by a specific commodity flow, Debreu (1951) and Shephard (1953) explain efficiency by a graphical representation of the production frontier: Debreu elaborates on output direction, Shephard emphasizes the principle of input

contraction in their respective contributions. Later, Farrell (1957) describes efficiency as a multi-step theory influenced by the Koopmans and Debreu. He breaks down efficiency into its parts, pointing out that cost-efficiency and production-efficiency are two distinct aspects of efficiency. Cost-effectiveness determines a cost-production minimization method for determining the input and output quantities.

Technical efficiency is one of the efficiency concepts that adopts the production activity through the given input level or a minimum quantity to produce the maximum output or the optimum production (Farell,1957). In other words, the optimum condition of inputs provides a favorable result. For instance, a company would be technically inefficient if it employed more people than it needed.

Figure 1: The efficiency concept




Source : The efficiency concept from: De Borger, Bruno, Kristiaan Kerstens, and Alvaro Costa (2002)

Figure 1 depicts the technical efficiency concept where the X and Y-axis represent the input combinations. Those inputs deduce the constant return to scale by assuming the double factor production. The QQ' is the isoquant that represents the same output from the production activity. Line A is the observation line to compare the number of input combinations. For example, if we found point A, which generates the same output as isoquant QQ', then we can regard point A as inefficient compared to point A' because it uses less input. The degree of technical efficiency is represented by the ratio distance OD/OE.

## 2.2 Stochastic Frontier Analysis (SFA)

Analysis of Stochastic Frontiers Analysis (SFA) is a parametric technique that employs standard production (cost) function. This method acknowledges that the production function represents the technically maximum feasible output level for any given intput. The SFA is capable of modeling function connections based on a variety of theoretical constraints (e.g., multi-input, multi-output, revenue function, cost function).

Meeusen and van den Broeck (1977), and Aigner, Lovell, and Schmidt (1977) assume that SFA is the production frontier model with two error components: statistical noise effect and technological inefficiency impact. Those concepts follow the distribution assumption. Meeusen and Van Den Broeck (1977) state that those inefficiency distributions follow the exponential distribution. On the contrary, Battese and Coelli (1977) argue that a half-normal distribution is for inefficiency. Therefore, Aigner, Lovell, and Schmidt (1977) determine inefficiency under both exponential and half-normal distributions. Later, Stevenson (1980) used the gamma and truncated normal distributions to estimate the inefficiency. The assumption of the inefficiency distribution will determine the value of each parameter.

In its application, SFA can be applied by using cross-sectional data or data observed at a certain time. In addition to cross-sectional data, SFA can also be applied using longitudinal data measured over time (panel data).

The use of SFA has varied over the time. In 1990, the SFA was used to measure efficiency between firms or producers (Battese & Coelli, 1992). Then, SFA analysis was also used to estimate the effect of exogenous variables on inefficiency (Huang & Liu, 1994). In several subsequent studies, SFA analysis was also applied by using functions to ignore the heterogeneity of unobserved data on component inefficiency. This is done to produce more reliable inefficiency values or to avoid mixing inefficiency with heterogeneity in unobserved data. Thus, our study will employ SFA to evaluate the efficiency of the bus routes by applying both Translog and Cobb-Douglas functions.

## 2.3. SFA Application on Efficiency of Transport Service

The Stochastic Frontier Analysis (SFA) is one of the methods that uses the economic function to measure efficiency. In its application, SFA considers the error variable into two components, namely the noise error component and the inefficiency error component. This consideration is necessary to get more reliable estimation results (Aigner, Lovell, and Schmidt, 1977).

In its implementation, SFA can use the production function or the cost function to measure the efficiency value of a predetermined decision making unit (unit of measure/what to compare/object of comparison). Hence, SFA is generally used to measure the efficiency of performance between companies (Ayadi, Sami (2015). Besides, SFA has also been widely applied to measure efficiency between pig farms (by Olsen and Henningsen's 2011). Both evaluations related to the financial and the production system, SFA become the essential tools to be utilized. Due to these factors, SFA applications are used extensively to determine the level of efficiency in various fields.

In the transportation field, SFA is utilized to evaluate the efficiency and to identify the effect of specific policies on service performance (e.g., railway, airlines, port, contracts, and subsidies). There are several implementations of SFA according to the type of transportation. Cullinane et al. (2006) estimate the efficiency of the world's largest container port in maritime transport. Ganzalez and Trojillo (2008) measure the port service facilities' efficiency in Spain.

In the railway sector, Farsi et al. (2005) observe the cost efficiency of the network industry with estimates of the 50 railway industries in Swiss during 13 years period. Smith (2012) applied SFA models in the European rail sector using panel data 1996 to 2006. It showed about a 40% gap in inefficiency in the European railway. In the airfield, Oum, Yan, and Yu (2008) identified the effect of the airport ownership on cost efficiency. Those study employed several world-class primary airport data for comparison. Another study identifies airport competition's impact on technical efficiency (Scotti et al., 2010).

Table 1 shows the application of SFA in previous studies which used various types of unit, variable, and functional analysis. In the transportation field, efficiency measurement is frequently done through comparisons between transportation operators.The unit analysis of SFA also takes into account the transportation operators from any mode of transportation (Farsi, Filippini, and Kuenzle (2006), Jarboui (2014), Holmgren (2013), Ayadi and Hammami (2015) and Sakai and Shoji (2010)).

In the case of the functional forms, the log-linear function or the Cobb-Douglas function has been used in the empirical study by Jorgensen, Pedersen, and Volden (1997). Later, the Translog function is broadly utilized as a flexible form with less restriction (Filippini, 2003). Aside from the function, the explanation of efficiency from the exogeneous variable is also conducted under the SFA assessment.

SFA models in the field of bus efficiency adopts various input and output variables. The number of drivers and workers, fuel consumption, and vehicles are the input variables, while vehicle mileage is the output variable (Viton, 1986). In another study, in evaluating a bus operator, vehicle kilometers and bus size were used as input variables to calculate the total cost as output variables (Jorgensen, 1997). Concering the same output of cost expenditure, Translog function is applied to use the labor price, energy cost, and capital as the input variable (Filippini, 2003). Thus, the vehicle-kilometer variable is commonly used as either input or output variable SFA in transportation services (Viton, 1981; Jorgensen, Pedersen, and Volden, 1997; Karlaftis, 2010; Sakai and Shoji, 2010. Empirical studies indicate that the bus kilometer is more cost elasticity

than the seat kilometer. Moreover, adding more number of seats is less expensive than adding bus kilometers (Filippini, 2003). The implementation of inputs and outputs also encounters that the use of bus kilometers to increase the bus fleet is cheaper than adding bus kilometers (Filippini, 2003).

SFA – regarding the differences in variables, functions, and unit analysis –has been evolved to allow various assumption in errors (Ayadi, 2015). This study examines the distinction between models that assume the error is fixed and models that assume the error is not fixed. In its application, the measurement of the efficiency with the SFA is also applied to various general policies. This analysis is performed to determine the impact of the policy on efficiency.

In addition to identifying the efficiency measurement from unit analysis, the impact of the particular policy on efficiency has been broadly observed. A previous study examines that the subsidy factor is related to the efficiency of buses (Jorgensen, 1997). The findings show that negotiated subsidy amount is less efficient than the standard amount (Jorgensen, 1997). Another related empirical study that used the cost function found that the subsidy has lower efficiency (Sakai, 2010). Those empirical findings underline that the subsidy has a potential negative impact on the optimization of service operation. Besides, the competition among the transport operators positively increase efficiency (Sakai, 2010).

The ownership factor determining bus service's efficiency is another interesting variable in the SFA. A case study in Switzerland indicates that private companies had more efficiency than public companies from 1991 to 1995 (Filippini and Prioni, 2003).

The research was conducted using data from 2000 to 2011. The results show that CEO behavior that is too optimistic has a negative effect on the company's technical efficiency (Jarboui, 2004)

## 2.4. Research Gap in the Literature

SFA has been widely used in evaluating transportation efficiency, i.e. land, sea, and air transportation efficiency. To evaluate the efficiency, the Cobb-Douglas and Translog production functions are frequently used. A number of previous empirical case studies on developed countries reveal that the SFA analysis with the Translog production function is preferable to the Cobb-Douglas function (Karlaftis, 2010; and, Sakai and Shonji, 2010). Research in developing countries that struggles with digitalization frequently comes across difficulties in collecting samples. This study investigates whether the Translog production function is preferable to the Cobb-Douglas function in Transjakarta public buses – a case study in a developing country for which the sample size is limited.

Table 1:SFA for transportation in the literature

| Author (year) | Data | Function | Input | Output | Efficiency | Insight |
|---|---|---|---|---|---|---|
| Viton (1981) | 67 bus transit systems fiscal year 1979/1980 | Translog production function | Driver, worker, fuel, vehicle | Vehicle-mile | Technical and allocative efficiency | Not consistence of two-side of error |
| Jorgensen, Pedersen, And Volden (1997) | Norwegian 170 bus companies on 1991 | Translog | Bus capacity, Vehicle, passenger -km | Vehicle/km | Productive inefficiency | No significantly different between public and private bus companies |
| Filippini And Prioni (2003) | 34 bus transit companies in Switzerland (1991-1995) | Translog Cost frontier | Labor price/annual Energy/ Capital price | Bus/km Seat/km | Technical efficiency | Private companies hold the more efficient |
| Farsi, Filippini And Kuenzle (2006) | 94 operators Switzerland (1986-1997) | Translog Cost frontier | Labor price/annual Capital price | Operational cost | Cost and scale efficiency | Unobserved firm particular effect on SFA |
| Karlaftis (2010) | 15 European public transport system (1990-2000) | Translog cost | Labor, maintenance, buses, | Vehicle/km | Technical efficiency | Competition increase the efficiency |
| Jarboui (2014) | 48 public transport company in 18 countries (2000-2011) | Production function | Revenue | Operating expenses Number of employee | Technical efficiency | Transport company CEOs effect on transport system |
| Holmgren (2013) | 26 swedish counties (1986-2009) | Cost function | Cost Subsidization Trip/person | Passenger/ km | Technical efficiency | The cost efficiency is fell 23% |
| Ayadi And Hammami (2015) | 12 Tunisian public transport (2000-2010) | Cost function | Capital Labor Energy | Seat/km | Cost efficiency | Regional bus transport is economically inefficient |
| Sakai And Shoji (2010) | 31 public transpot companies 1990-2006 | Cost function | Price of labor Price of fuel Price of capital Price of service Price of materials | Vehicle/km | Cost efficiency | Subsidy is negatively impact the cost efficiency |

# Chapter 3. Methodology

This study was conducted to evaluate the performance of public buses in Jakarta, Indonesia. The purpose of this study is to evaluate the technical efficiency of the bus route in providing service. The results showed which routes have higher technical efficiency and which routes have lower technical efficiency.

We begin the research by identifying the efficiency measurement using the Stochastic Frontier Analysis (SFA) as the foundation of the evaluation. Afterwards, the differences between the DEA and SFA – as the types of frontier methods that are commonly use – are discussed. Eventually, the SFA method, including its functions and formulas, is elaborated.

## 3.1 Efficiency measurement

In the past ten years, various methods for determining efficiency have been proposed. Those methods have one thing in common, namely the concept of the frontier. The best-practice frontier is the most efficient combination of inputs and outputs. Farrell (1957) claims that the best-practice frontier is a way to compare the unit analysis to see whether the industry is working well or not.

Given the context of the benchmarking idea, a set of methodologies can be used to define the best practice frontier. The foremost common methods for estimating the frontiers are the Data Envelopment Analysis (DEA) and the Stochastic Frontier Analysis (SFA) (Cullinane et al., 2002). A summary of the taxonomy benchmarking analysis has been found to be a means of increasing other researchers' understanding of DEA and SFA analysis.

Table 2: Taxonomy Benchmarking

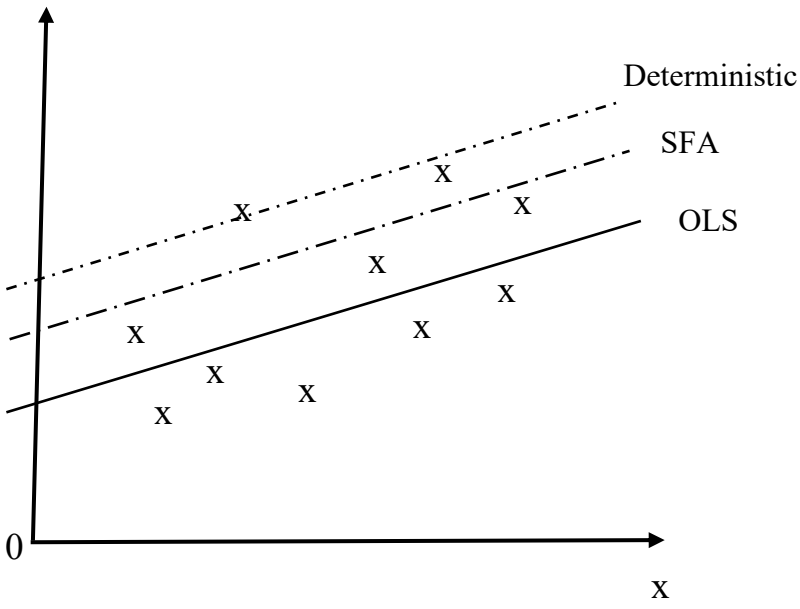
| | Deterministic | Stochastic |
|---|---|---|
| Parametric | Corrected Ordinary Least Square (COLS) | Stochastic Frontier Analysis (SFA) |
| Non-parametric | Data Envelopment Analysis (DEA) | Stochastic Data Envelopment Analysis (SDEA) |

In order to explain the definition of the benchmarking in each model, it is necessary to make a distinction between statistical methods and non-statistical methods. Statistical methods use mathematical models, functions, and techniques, while non-statistical methods do not. In discussing statistics, popular wisdom distinguishes between the parametric and the non-parametric. The parametric technique anticipates assembly possibilities based on previous knowledge, whereas the non-parametric method relies on an unknown distribution or less prior knowledge. Another difference between stochastic and deterministic models is that the stochastic technique assumes data estimation with an error variable while the deterministic method assumes all data is precisely observed.

From the two definitions of deterministic or stochastic and parametric or non-parametric, the benchmarking method can be illustrated according to Table 2. Each model has different behavior toward noise data. Table 2 shows the deterministic parametric model produced using the COLS, COLS estimates the value using ordinary regression (Aigner and Chu, 1968 and Lovell, (1993) and Greene (1990, 2008). Those values were computed using the previous model, which assumes that the linear frontier lies within the transformation average estimator. The parametric Stochastic Frontier Analysis (SFA) applies the frontier analysis according to the econometric concept and mathematical functions (Aigner, et al., 1977; Battese and Coelli (1992); Coelli et al (1998)). In the SFA method, the analysis error is divided into a noise component (from missing data irregularities) and an inefficiency component (from input changes to output) (Aigner et al., 1977). Non-parametric deterministic strategies use linear programming by enclosing the data set or Data

Envelopment Analysis (DEA) (Charnes et al., 2003; Deprins et al (1984)). The DEA is a simple mathematical form. It refers to a benchmarking method that uses minimal extrapolation, but it may requires a large number of data to obtain a reliable result. Furthermore, Land et al. (1993) & Olesen and Petersen (1995), Fethi et al (2001) Describe Stochastic Data Envelopment Analysis as stochastic and non-parametric. The analysis combines a flexible structure and a variety of noisy data.

Figure 2: A comparison of the model parameters



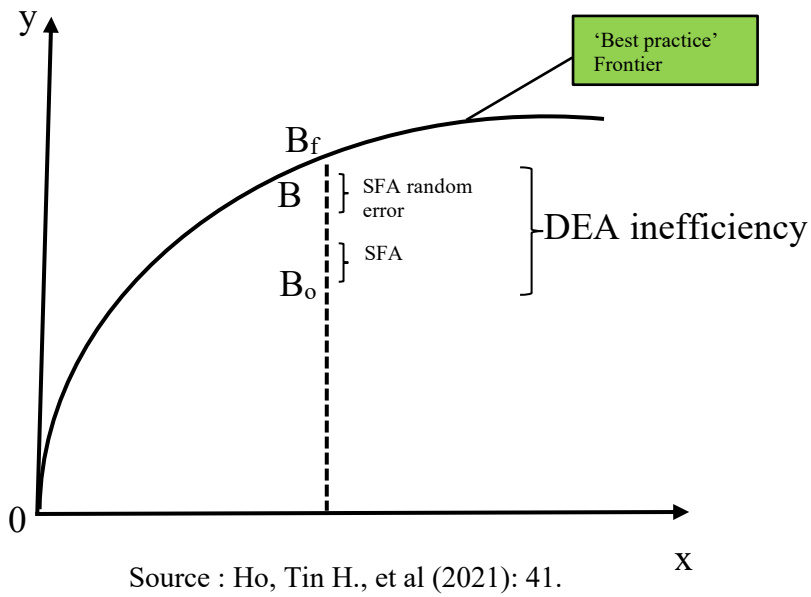

Source : Bogetoft, Peter, and Lars Otto (2010)

The comparative frontier model is depicted in Figure 2; the graphic shows the different estimate parameters from each frontier model. the Stochastic Frontier occupies the middle ground between the deterministic and conventional Least Square approaches. It is notable that the SFA also treats the error component as the inefficiency and the noise component. Additionally, the SFA method becomes more flexible to make assumptions from existing data.

## 3.2 Stochastic Frontier Analysis (SFA) Versus Data Envelopment Analysis (DEA)

The Data Envelopment Analysis (DEA) and the Stochastic Frontier Analysis (SFA) are frequently applied in the evaluation of the transportation service on land or air transportation (De Borger et. al, 2002). This is because SFA and DEA can be used for multiple inputs and outputs, which is the reason why these two methods are frequently used.

Figure 3: Comparison between DEA and SFA




Source : Ho, Tin H., et al (2021): 41.

In this study, the SFA is applied rather than the DEA; the preference for using SFA is explained in the following discussion by describing the picture regarding the error treatment. The figure 3 illustrates the difference between the two methods: in DEA, the error structure is only treated as the one error component, but in SFA, the error variable described is regarded as both random error and inefficient error. In DEA, noise biases inefficiency component measurements, which can affect the predicted duality between the production function and the cost function (Greene, 2008). Another reason is that the data used in this method is very limited, so applying a more flexible model is an alternative to get reliable results.

## 3.3 Stochastic Frontier Approach

The Stochastic Frontier Analysis (SFA) is a mathematical function that measures efficiency by adhering to an econometric concept. SFA with component error structure (statistical noise and technical inefficiency) was first introduced by Battese and Corra (1977). Although the concept initially appeared, there were several different assumptions regarding the distribution of component inefficiency errors. Meeusen and van den Broeck (1977) assume the exponential distribution, and Battese and Coelli (1995) use half normal distribution, while Aigner, Lovell and Schmidt (1977) use both assumptions.

Following Battese and Coelli's (1995) work on the estimation of technical efficiency using a stochastic frontier approach, the stochastic frontier production function for panel data is as follows:

$$y_{it} = f(x_{it}, t; \beta) \exp(v_{it} - u_{it}), i = 1,2, \dots, N \;\; t = 1,2, \dots, T \tag{1}$$

Each firm represents $\mathrm{i} = 1 \dots \mathrm{N}$ with the t= 1..T. Firm at time t in this work, we consider the service among the bus routes as the unit analysis, whereas each bus route represents $y$ as the output production scalar on this work we consider the passenger-kilometer. The explanatory variable of the output variables is then considered as the input variable. Hence, the input vector represents the $x$ symbol, and the total error represents $\varepsilon = v - u$. This observation is examined from the service provided to the demand attraction. The error component $u$ defines production inefficiency or inefficiency of a firm activity, and the distribution of $u$ is adjusted to a half-normal distribution.

Furthermore, $v$ represents noise in the observational data or the natural production process and is assumed to have the following normal distribution. This study's noise variable may consist of extreme weather conditions or route construction that impact the number of Transjakarta passengers. Both $u$ and $v$ are assume as the independent variables.

### 3.3.1 Stochastic Production Function: Cobb-Douglas and Translog

Transportation efficiency and productivity are inextricably linked to the industrial or production function. The Cobb-Douglas and Translog production function (cost) are frequently performed to measure efficiency. To comprehend the idea, Cobb-Douglas and Translog production functions will explain.

$$y_i = A \prod_{k=1}^{k} x_{ik}^{\beta k} \exp(\varepsilon_i) \tag{2}$$

Equation (2) depicts the production function formula. The vector firm product is presented in $y_i$, with the input vector $x_{ik}^{\beta k}$ and the residual element "$A$" e $\beta_k$ parameter determined $\varepsilon_i$. The $\beta_k$ measures the number of product that interacts with the input by using this equation (Varian, 2003).

The input vector on the production function is derived using the Cobb-Douglas function, as illustrated in Equation (3). Thus, it is assumed that each input vector is homogeneity (linear) without any marginal productivity.

$$\log(y_i) = \beta_0 + \beta_1 \log x_1^{it} + \beta_2 \log x_2^{it} + \beta_3 \log x_3^{it} + v_{it} + u_{it} \tag{3}$$

Another model of production function is introduced by Christensen et al (1973) that suggest the use of the transcendental logarithmic (Translog) on Equation (4). The product vector is represented by $y$ with the $x$ corresponding to the input vector, the unknown estimate parameter is represented by $\beta_i$, and the $\beta_{ij} = \beta_{ji}$with the error term is represented by $\varepsilon_i$. The input variables in the Translog function consider the elasticity relationship between the pair or the homogeneity of the parameter (Albuquerque, 1985). The Translog function can also consider the marginal productivity. However, the Translog function may create multicollinearity as a result of the mathematical manipulation used in econometrical estimation (Martins et.al, 2012).

$$\ln y = \beta_0 + \sum_{i=1}^{n} \beta_i \, ln \, x_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} \ln x_i \ln x_j + \varepsilon_i \tag{4}$$

This study indicates that the total error represents the natural input and output manufacturing process error $\varepsilon = v_{it} - u_{it}$. U denotes production inefficiency or firm distortion; the noise component from the random variable is assumed to be iid N $(0, \sigma_v^2)$; the inefficiency model is the non-negative random variable $u_{it}$ and it is assumed to fit the truncated non-negative stochastic variable with mean $m_{it,}$ variance $\sigma_u^2$.

The random variable weight inefficiency component represents the observed whether the prior model of the explanatory variable is determined from $\gamma = \frac{\sigma_u^2}{\sigma_v^2} = \frac{\sigma_u^2}{\sigma_v^2 + \sigma_u^2}, (0 \leq \gamma \geq 1)$. If the lamda *(sigma u/sigma v)* result is close to zero, the difference between the actual output of the route and the maximum possible output is primarily due to an uncontrollable factor (noise component). Yet, if the result is closer to one, the total error in the frontier production function is dominated by the inefficiency component.

### 3.3.2 Firm Technical Efficiency

The efficiency level is derived from the ratio of firms' average plan execution (input) to their average output (output) (compared to the ratio of inputs and outputs) (Battese, George E., and Tim J. Coelli. 1988). In addition, the efficiency level is considered from 0 to 1. The following equationis formulated to calculate efficiency:

$$\mathrm{T}E_i = \frac{E(Y_{it}^{*}|U_i, x_{it},\ \ t = 1,2,\dots)}{E(Y_{it}^{*}|U_i = 0,\ x_{it},\ \ t = 1,2,\dots)'} \tag{5}$$

$$technical\ inefficiency\ = 1 - \mathrm{T}E_i$$

At time t, the output of production for each enterprise is Y, with the $\mathrm{T}E_i$ between 0 and 1. For instance, if a company's productive efficiency is 0.75, it suggests that an ideally efficient corporation with comparable input values may produce an average of 75% of its output.

Those techniques are introduced by Battesse and Coelli (1988) as an initial idea for estimating a firm's efficiency. such notions are being developed in order to have a more reliable application (e.g., time-varying).

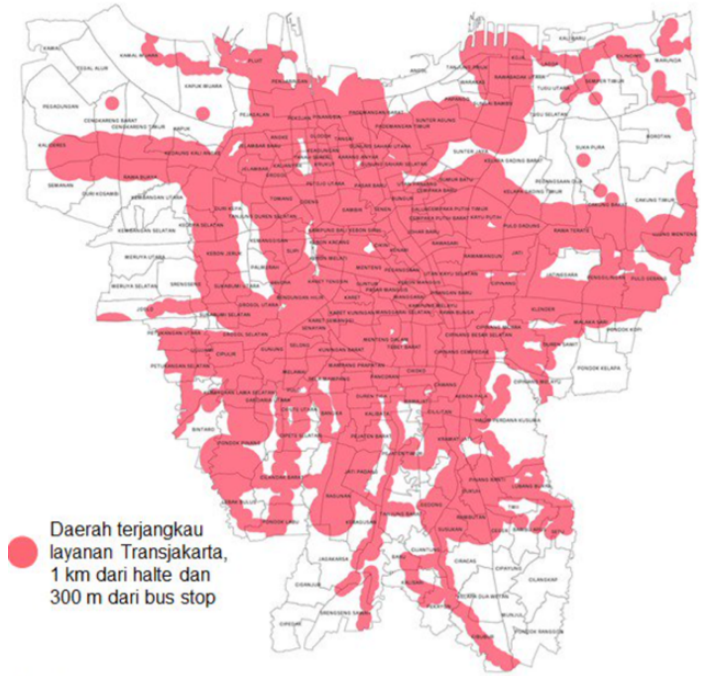
# Chapter 4. Application

The purpose of this research is to estimate the service efficiency of buses in Jakarta; the various bus routes serve as the unit of analysis. This study applies Stochastic Frontier Analysis (SFA) using the production function to achieve this goal. This section is presented in four parts. In the first part of this section, we will describe the case study area. The second section identifies route selection for measuring efficiency, route classification, and the input-output variables. The third section describes the procedure and model development for estimating the efficiency of bus operation.

## 4.1 Study Area

The Jakarta Bus Rapid Transit (BRT) –commonly known as Transjakarta – began operations in February 2004 and became the Southeast Asia and South Asia's first bus rapid transit system. Transjakarta expanded its service in 2018 to reach up to 58% of Jakarta's metropolitan area shown in Figure 4. Seven out of every ten inhabitants are served by the Transjakarta service. As a result, service transportation is evolving to connect more sites and provide accessibility. Transjakarta had 247 routes in the metropolitan region's 10 cities and two counties in 2019. All services are managed by Regional Owned Enterprises (BUMD) and public bus authorities in partnership with many operators.

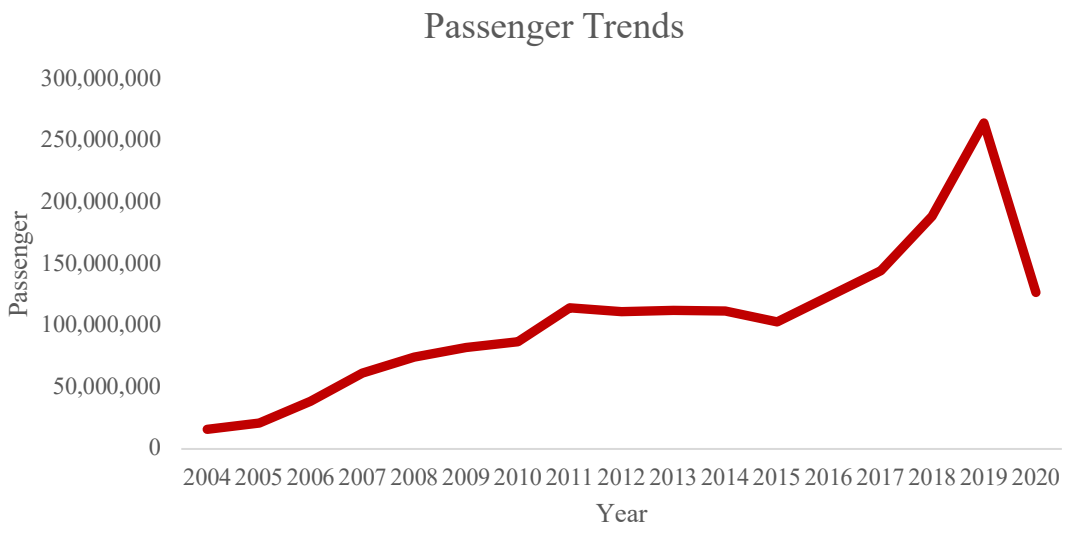
Figure 4: Transjakarta catchment area




Source : ITDP Indonesia

The Figure 5 illustrates the increasing number of passengers over the years. This indicates that the service from 2004 as the initial year continues to increase until 2011 by 114,783,824 passenger. The increase in passengers from 2010 to 2011 by roughly 32% was attributed to Transjakarta facility upgrades such as boosting Transjakarta service, which policy governed the odd-even bus number plate transportation system at the time (databox.com). From 2014 to 2015, the number of passengers slightly decreased by 19,019,512. Those are due to the road construction on the primary routes on Transjakarta (routes 1 and 9), which made people prefer using private vehicles (transjakarta.com). Then, it continues to increase by 264,653,712 passengers in 2019—due to the increasing number of routes and integration services with other public transportation mode. However, due to the COVID-19 pandemic in 2020, the number of passengers fell by 50% from the number of passengers in 2019.

Figure 5: Transjakarta passenger trends




Source : Transjakarta.com

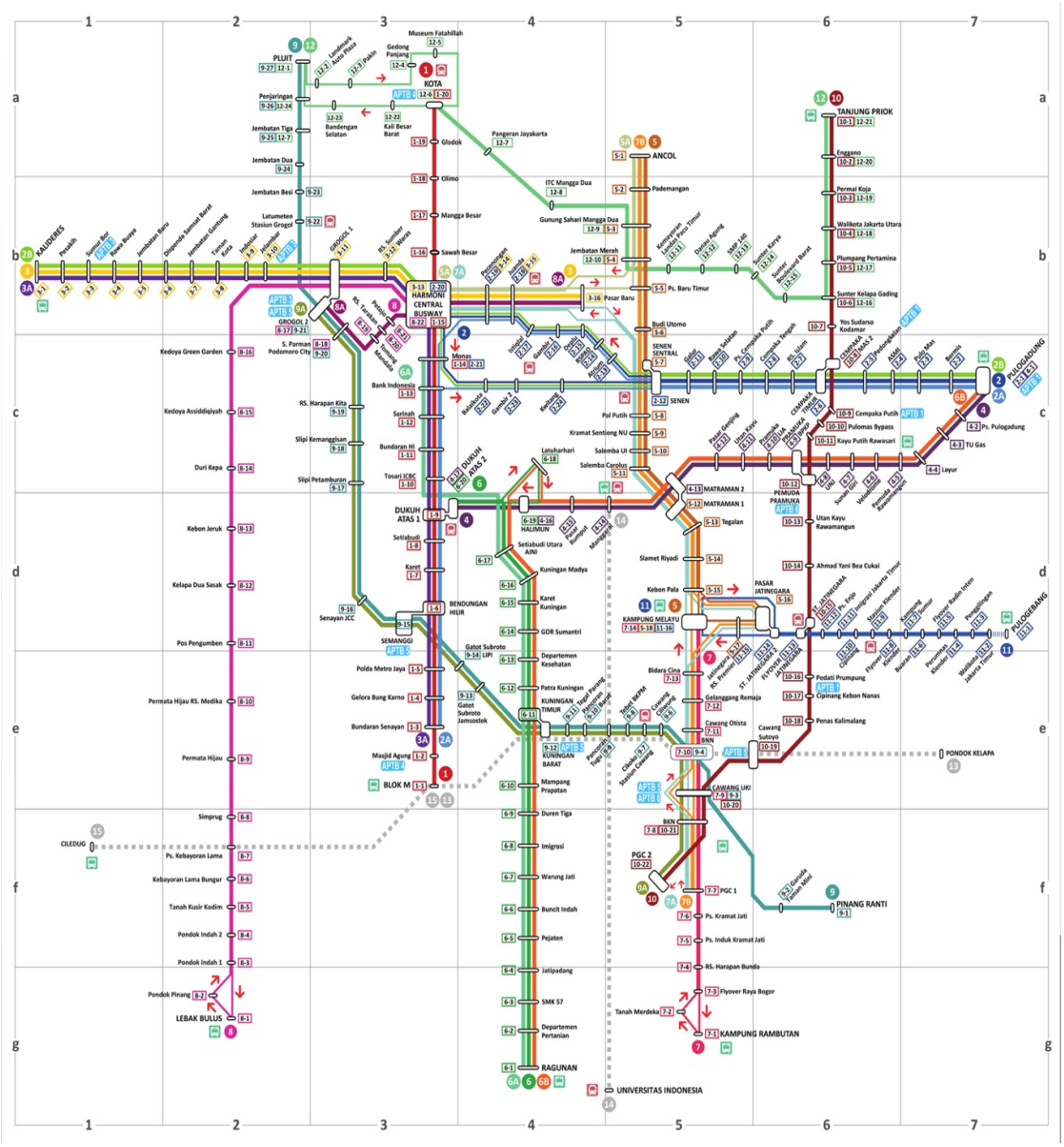
The increasing number of Transjakarta's passengers over the last five years, as illustrated in Figure 5, shows that Transjakarta is performing pretty well overall. In particular, the objective of this research is to determine whether the services operated efficient or not.

## 4.2. Data Description

This section describes detailed data including the entire service bus route, route selection, route group construction, and input-output variable selection. The second section then elaborates on the model's development based on observations. In the last section, several assumptions that follow the empirical approach are described.

### 4.2.1 Transjakarta Routes

Figure 6: Transjakarta bus network maps




Source :http://www.transportumum.com/jakarta/wp-content/uploads/2011/02/petaTransjakarta-busway-juli-2014r.jpg

Figure 6 depicts Transjakarta network maps serving *Jabodetabek* by connecting five surrounding cities (Jakarta, Bogor, Depok, Tangerang, and Bekasi). As a result, Transjakarta has been operating 248 routes since 2020, each of which is divided into many services. Furthermore, Transjakarta service is integrated with other modes of transportation (e.g., MRT, LRT). As can be seen in the Table 3, Transjakarta provides nine separate services, ranging from Bus Rapid

Transit (BRT), minibus, bus integration, premium county feeders (Royal Feeder), and the local bus feeder. Among the various bus routes; the primary one is Bus Rapid Transit (BRT) with priority lane services that run through the city center. The feeder service consists of mini-buses that travel along the local roads. Intercity feeders include the bigger Jakarta feeder and the royal bus. Tour buses also cover transit services and tourist attractions in the metropolitan region. In addition, Transjakarta Care also provides free services for passengers with disabilities.

Table 3: Transjakarta category services with the number of bus and routes in 2020

| CATEGORY | SERVICE TYPES | NUMBER OF BUS | NUMBER OF ROUTES |
|---|---|---|---|
| BRT | BRT routes | 783 | 54 |
| Minibus | Minibus free feeder | 1,368 | 69 |
| Bus Transport integration | Overlapping routes bus with the BRT bus stop | 602 | 69 |
| Greater Jakarta Bus | city Feeder | 193 | 14 |
| Condominium Feeder | Free feeder routes | 47 | 21 |
| Royal Bus | Premium counties feeder | 82 | 13 |
| Tour Bus | Tour bus along the landmark | 25 | 7 |
| Special events Bus | Special event | 31 | - |
| Transjakarta Cares | | 18 | - |
| Total | | | 247 |

### 4.2.2 Selection of Routes for Efficiency Measurement

According to Governor Regulation Number 63 of 2014, the public authority has replaced the consortium system in Jakarta's public bus operating service per route. The Jakarta bus authorizes the provision, control, and regulation of all bus operation along all routes. Therefore, the other firm (non-Jakarta public bus) rents multiple buses to the Transjakarta company (municipally-owned corporation) on a per-kilometer basis or contract-based. In light of this, benchmarking analysis is an evaluation carried out by comparing various production entities with other production entities. Corporations, organizations, projects, decision-making units, or individuals may be the unit of analysis for any entity, a generic and adaptable variable to assess the quantity of input into the output (Bogetoft and Lars, 2010). The supply of bus service along various routes is considered the unit of analysis in this study, in accordance with the research case and the idea of unit analysis. Hence, each unit of analysis evaluates the efficiency of service operation across bus routes. Based on empirical investigations, the evaluation of bus routes efficiency using DEA analysis has been addressed by Seth (2007) on the efficiency of the bus on 60 routes. In addition, Kim, Sukhee, and Taeil Sim (2021) applied the same approach using 87 bus routes.

Due to a number of factors, this research will not be able to include all routes from the entire Transjakarta bus operation. Hence, there are various factors to consider when deciding whether data to be included or excluded in this investigation. This section will identify the bus route services that are included and describe the routes that are excluded as follows:

First, the data covers the BRT route, starting from route number 1 to route number 12. This is because the BRT line has been the main service for Transjakarta since its inception, and all data is available.

Table 4: Route classification

| CLASSIFICATION | ROUTES | | | | | |
|---|---|---|---|---|---|---|
| BRT | 1 | 2 | 3 | 4 | 5 | 6 |
| | 7 | 8 | 9 | 10 | 11 | 12 |
| LARGE-SIZE | 10B | 10K | 11B | 11C | 11D | 11K |
| | 11M | 11Q | 12A | 12B | 12F | 1A |
| | 1B | 1C | 1E | 1F | 1H | 1M |
| | 1N | 1Q | 1R | 2B | 2F | 3A |
| | 3E | 4B | 4F | 5B | 5F | 5M |
| | 5N | 6H | 6M | 6N | 7A | 7B |
| | 7C | 7D | 7P | 8D | 8E | 8K |
| | 9D | 9E | 9H | D21 | S11 | S21 |
| | T11 | | | | | |
| SMALL-SIZE | JAK.01 | JAK.02 | JAK.03 | JAK.04 | JAK.05 | JAK.06 |
| | JAK.07 | JAK.08 | JAK.09 | JAK.10 | JAK.10A | JAK.10B |
| | JAK.11 | JAK.112 | JAK.117 | JAK.12 | JAK.13 | JAK.14 |
| | JAK.15 | JAK.16 | JAK.17 | JAK.18 | JAK.19 | JAK.20 |
| | JAK.21 | JAK.22 | JAK.24 | JAK.25 | JAK.26 | JAK.27 |
| | JAK.28 | JAK.29 | JAK.30 | JAK.31 | JAK.33 | JAK.34 |
| | JAK.35 | JAK.36 | JAK.37 | JAK.38 | JAK.39 | JAK.40 |
| | JAK.41 | JAK.42 | JAK.43 | JAK.44 | JAK.45 | JAK.46 |
| | JAK.47 | JAK.49 | JAK.50 | JAK.51 | JAK.52 | JAK.53 |
| | JAK.54 | JAK.56 | JAK.58 | JAK.59 | JAK.60 | JAK.61 |
| | JAK.64 | JAK.71 | JAK.72 | JAK.73 | JAK.74 | JAK.75 |
| | JAK.77 | JAK.80 | JAK.84 | JAK.85 | | |

Second, the Non-BRT service is represented by a symbol with a number followed by an alphabet (e.g., 2E, 10B). The service operates along the entire city of Jakarta, which also has feeders between BRT and feeders from other regions. Some Non-BRT route services are not available due to traffic engineering schemes implemented in Jakarta to reduce traffic (e.g., one-way streets). There are also other routes that provide incomplete data due to the lack of a data collection mechanism in the field. The specific information regarding routes selection is displayed in the Appendix 1.

Another non-BRT is the Royal Trans as a Transjakarta premium feeder service that operates across large distances. Unfortunately, this data is not available due to the lack of a transport permit for the data collection mechanism. Another service is the county feeder which represents the route name from the alphabet followed by the number (e.g., B15, D11). Some service data are incomplete due to the lack of county feeder system data collection. Consequently, this analysis solely takes into account some complete data.

Other special services, such as the tour bus (BW) and the free service bus (GR), are only available during holiday seasons and special government occasions. Therefore, these services were excluded from the analysis to prevent biased study results. Several route statistics data were absent due to road construction, service renewal, and questionable regulation during the pandemic. As indicated in the Table 4, only 131 routes were utilized to determine the service performance in this investigation.

### 4.2.3 Route Classification

This study consisted of 131 bus routes for SFA. Hence, to minimize misinterpretation of the result, these bus routes are divided into two groups according to the route characteristics.

- Routes using large-size buses include vehicles having a capacity of 30 seats on a single bus and 60 seats on a double bus. The lane network is around 15 km in routes and 29 km in routes 9. Those groups include the non-BRT routes covering services throughout central Jakarta, including other feeder areas or integration routes between other public transport.
- Routes with a small group refer to service routes comprised of a minibus with 11 seats. Those services involve local feeder integrated public transport; thus, the operation uses a minibus with a route length of 14 km to 33 km. This minibus is operated freely and is integrated with other Transjakarta services.

### 4.2.4 Selection of Input-Output Variable

In order to evaluate the technical efficiency of routes, it is necessary to determine the input and output variables. The appropriate input-output selection is important for constructing a reliable analysis using the SFA method. As a result of the previous transportation industry, empirical investigations can contribute to the selection of variables for a better analysis.

In the evaluation of urban transport, output variables such as vehicle mileage, passenger-kilometers, seat kilometers, or operating expenses are usually used (Viton, 1981; Jorgensen, Pedersen and Volden, 1997; Filippini and Prioni, 2003; Farsi, Filippini and Kuenzle, 2003; Karlaftis, 2010; Holmgren, 2013; Jarboui, 2014; Ayadi & Hammami, 2015; Sakai & Shoji, 2010). In another empirical studies, the variable input such as the number of drivers, workers, fuel, vehicle, labor, vehicle-kilometer, revenue, subsidy, and the trip is frequently applied to evaluate the efficiency of the operation (Viton, 1981; Jorgensen, Pedersen and Volden, 1997; Filippini and Prioni, 2003; Farsi, Filippini and Kuenzle, 2003).

The aim differs from the variables – the operating expenditures variable is the cost-oriented indicator with the total cost as output, whereas the production-oriented indicator includes the vehicle-kilometer and seat kilometer as outputs.

As the demand-oriented variable, passenger-kilometers would better indicate the efficiency of each route. Passenger-kilometer are often used in various studies, including Bhattacharyya, A., Kumbhakar, S. C., and Bhattacharyya, A (1995), De Jong, G., and Cheung (1999), and Levaggi (1999). (1994).

The annual vehicle-kilometer variable, which is determined by multiplying the route length by the number of trips, is decided as the input variable. According to an empirical investigation, Jorgensen, Pedersen, and Rolf (1997) used the vehicle kilometer as an input variable. The yearly bus capacity per route is computed using seating capacity and standing capacity. De Jong, G., and Francis Cheung (1999) and Gathon (1989) both detected these in input variables from urban transportation assessment. Concerning the purpose of this study, we took vehicle and bus seat kilometers to represent the service performance of each route. In addition, the population of the service area is potential passengers along the route.

As a result, our analysis will employ the variable as follows:

- *Passenger-kilometer*

  An input variable is the yearly vehicle-kilometer variable, which is calculated by multiplying the route length by the number of trips. The vehicle-kilometer is used in two ways, according to the empirical study. First, it is seen as an input variable in the cost function (Jørgensen, Pedersen, and Rolf 1997). Second, it is investigated as an output variable (Costa, Aâ.And Markellos, R.N., 1997).

- *Number of seats/ bus capacity*

  The efficiency evaluation estimates below the annual number of bus capacity per route calculated from the seating capacity and standing place. De Jong, G., and Francis Cheung (1999) and Gathon (1989) both recognized these as input factors in urban transportation measurements.

- *Vehicle-kilometer*

The number of passenger kilometers is calculated using the number of capacity bus and vehicle kilometers as an input variable. These passenger-kilometers represent the annual number of passengers on the entire route. The wide application of passenger-kilometers is often used in several studies such as; Bhattacharyya, A., Kumbhakar, S. C., & Bhattacharyya, A (1995), De Jong, G., and Cheung (1999) and Levaggi (1994).

- *Service area population*

The United States national transit database measures transit services in terms of the population served, and the area covered (square miles) taking into account the population of the service area. The Americans see the Americans with Disabilities Act of 1990 (ADA) as enclosing the routes 3/4 miles on either side of a ¾ mile radius circle centered on each station. Consequently, the service area of this study is calculated from 3/4 of the area along the bus route.

The population density is obtained from the Jakarta population density. Therefore, the detailed service area population is as follows:

$$1.207\ x\ 2\ x\ route\ length\ x\ Jakarta\ pop.density$$

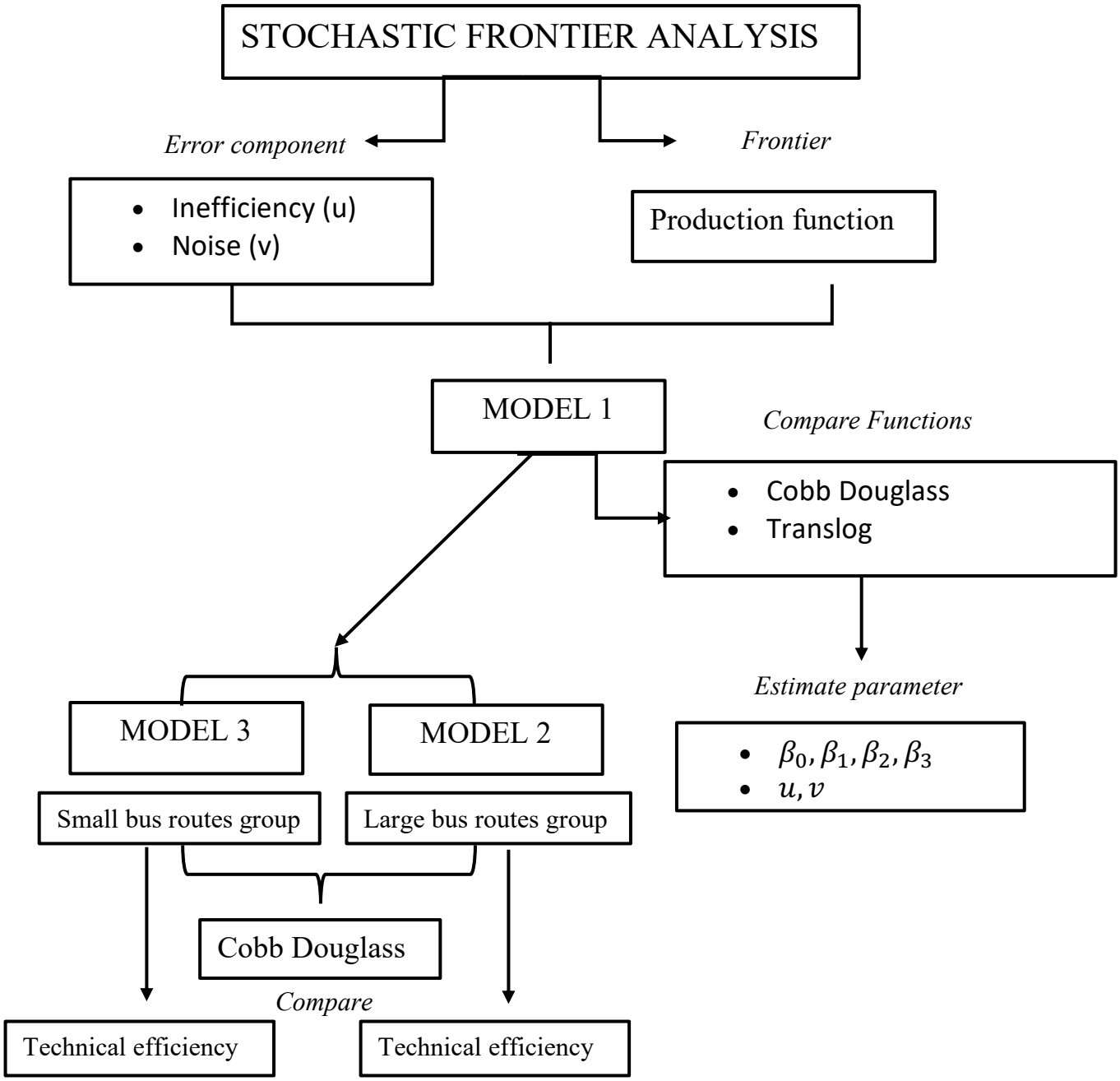
Note:

- $\frac{3}{4} mile$ (both side) convert in kilometer = 1.207
- $x$ 2 (both side)
- $Jakarta\ population = \frac{Total\ population}{Land\ area\ covered}$

*"A measure of access to transit service in terms of population served and area coverage (square miles). The reporting transit agency determines the service area boundaries and population for most transit services using the definitions contained in the Americans with Disabilities Act of 1990 (ADA), i.e. a corridor surrounding the routes 3/4 of a mile on either side, or for rail, a series of circles of radius 3/4 mile centered on each station Transit agency reporters are required to submit service area information",* (Source: US national transit of data base (NTD)).

## 4.3 Modeling

Figure 7. Evaluating the efficiency of bus operation routes flow chart



This study employs SFA, a methodology that divides error into two components: inefficiency and noise. The production function model is also used to estimate the parameters in this study. This research will be divided into three models. The first model uses all data routes, 131 routes. In data analysis, model 1 uses two production functions, namely Cobb-Douglass and Translog. In model 2, the analysis uses the Cobb-Douglass production function on large bus route data, 49 routes. Then, model 3 uses small-size bus route data, 70 routes and applies the Cobb Douglass production function. Details of each model are listed in Table 6. Then, the technical efficiency of large and small group bus routes can be determined, and the two groups' technical efficiency can be compared.

### 4.3.1 Cobb-Douglas Function

$$\ln(y_i) = \beta_0 + \beta_{seat} \ln x_i^{seat} + \beta_{veh} \ln x_i^{veh} + \beta_{SAP} \ln x_i^{SAP} + v_i - u_i \quad (6)$$

The $y_i, \beta_0, \beta_{seat}, \beta_{veh}, \beta_{SAP}$ represent the passenger-kilometers, the number of seats, vehicle-kilometers, population of the i-th route service area, and $\beta$ are unknown parameter to be estimated.

### 4.3.2 Translog Function

$$\begin{aligned} lny_{it} = \beta_0 &+ \beta_{seat}\, lnx_i^{seat} + \beta_{SAP}\, lnx_i^{SAP} + \beta_{veh}\, lnx_i^{veh} + \frac{1}{2}\beta_{seat,seat}\, lnx_i^{seat} \\ &* \, lnx_i^{seat} + \beta_{seat,SAP}\, lnx_i^{seat} * \, lnx_i^{SAP} + \frac{1}{2}\beta_{SAP,SAP}\, lnx_i^{SAP} * \, lnx_i^{SAP} \\ &+ \beta_{SAP,veh}\, lnx_i^{SAP} * \, lnx_i^{veh} + \frac{1}{2}\beta_{veh,veh}\, lnx_i^{veh} * \, lnx_i^{veh} \\ &+ \beta_{seat,veh}\, lnx_i^{seat} * \, lnx_i^{veh} + v_i - u_i \end{aligned} \quad (7)$$

Where $y_i, x_i^{seat}, x_i^{SAP} and\ x_i^{veh}$ represent the passenger-kilometer, the number of seats, service area population, vehicle-kilometer of the routes and $\beta$ are unknown parameters to be estimated

All estimates for the Stochastic Frontier Analysis (SFA) were generated using R studio version 1.4 in this study that was proposed by Aigner, Lovell, and Schmidt (1976) and Battese and Coelli (1992, 1995). This study uses the frontier package in R studio to estimate the investigation parameters in order to produce credible results. In addition, this study uses diagrams, to illustrate the result better.

# CHAPTER 5 RESULT

This chapter presents the result of applying the Stochastic Frontier Analysis (SFA) concept to assess the efficiency of the bus route described in Chapter 4. This section estimates parameters using two production functions (Cobb-Douglas and Translog) and variables such as passenger-kilometer, number of seats, vehicle-kilometer, and service area population. Different groups of bus route characteristics are also considered to measure efficiency. Moreover, the analysis focuses on finding the most efficient and inefficient routes. Firstly, this research develops the SFA models and the results from the Cobb-Douglas and Translog function will be compared. Therefore, the preferable function is selected to analyze each group route. Secondly, the SFA is carried out for each group of bus routes of Transjakarta. Thirdly, the SFA of efficiency is carried out for each route. Lastly, suggestions are made to improve the service provision from the Transjakarta efficiency analysis. Potential improvements to increase the efficiency of Transjakarta and the provider's benefit are aimed.

## 5.1 Model Specification

When measuring efficiency, the production function or cost function must be specified. There are some functions for estimating the parameters of the production. This section provides estimations using the Cobb-Douglas and Translog production functions. After analyzing both approaches, the more robust model is selected to calculate the technical efficiency. Therefore, the analysis is carried out as seen in Table 7.

The analysis is divided into three models. The first model uses all data routes, 131 routes. In data analysis, model 1 uses two production functions, namely Cobb-Douglass and Translog. In model 2, the analysis uses the Cobb-Douglass production function on large bus route data, 49 routes. Then, model 3 uses small-size bus route data, 70 routes and applies the Cobb Douglass production function. Details of each model are listed in Table 6.

Table 5: Descriptive Statistics of The Sample Transjakarta 2020

| Classification | Pass-Km (Billion) | Veh-Km (Million) | Seat (Million) | Service Area Pop (Million) | N |
|---|---|---|---|---|---|
| BRT | 41,033 | 5.913 | 17.375 | 1.904 | 12 |
| NON-BRT | 169.674 | 0.596 | 1.533 | 1.534 | 49 |
| MINIBUS | 1,226 | 1.954 | 0.914 | 1.388 | 70 |

For estimation of the parameters, this study analyzes three models according to the different routes' characteristics as follows:

Table 6: Characteristic model

| **Parameter** | **Model 1** | **Model 2** | **Model 3** |
|---|---|---|---|
| Data | All size routes | Routes with Large size buses | Routes with Small size buses |
| Production Function | Cobb-Douglas & Translog | Cobb-Douglas | Cobb-Douglas |
| N. sample | 131 | 49 | 70 |

The model equation from each group is as follows:

**Model 1**

*Cobb-Douglas function*

$$\ln(y_i) = \beta_0 + \beta_{seat} \ln x_i^{seat} + \beta_{veh} \ln x_i^{veh} + \beta_{SAP} \ln x_i^{SAP} + v_i - u_i \tag{8}$$

*Translog function*

$$\begin{aligned} lny_{it} = \beta_0 + \beta_{seat}\, lnx_i^{seat} + \beta_{SAP}\, lnx_i^{SAP} + \beta_{veh}\, lnx_i^{veh} + \frac{1}{2}\beta_{seat,seat}\, lnx_i^{seat} \\ * \; lnx_i^{seat} + \beta_{seat,SAP}\, lnx_i^{seat} * \; lnx_i^{SAP} + \frac{1}{2}\beta_{SAP,SAP}\, lnx_i^{SAP} \\ * \; lnx_i^{SAP} + \beta_{SAP,veh}\, lnx_i^{SAP} * \; lnx_i^{veh} + \frac{1}{2}\beta_{veh,veh}\, lnx_i^{veh} * \; lnx_i^{veh} \\ + \beta_{seat,veh}\, lnx_i^{seat} * \; lnx_i^{veh} + v_i - u_i \end{aligned} \tag{9}$$

**Model 2**

$$\ln(y_i) = \beta_0 + \beta_{seat} \ln x_i^{seat} + \beta_{veh} \ln x_i^{veh} + \beta_{SAP} \ln x_i^{SAP} + v_i - u_i \quad (10)$$

**Model 3**

$$\ln(y_i) = \beta_0 + \beta_{seat} \ln x_i^{seat} + \beta_{veh} \ln x_i^{veh} + \beta_{SAP} \ln x_i^{SAP} + v_i - u_i \quad (11)$$

- *No-Veh (without vehicle-kilometer)*

$$\ln(y_i) = \beta_0 + \beta_{seat} \ln x_i^{seat} + \beta_{SAP} \ln x_i^{SAP} + v_i - u_i \quad (12)$$

- *No-Seat (without the number of seats)*

$$\ln(y_i) = \beta_0 + \beta_{veh} \ln x_i^{veh} + \beta_{SAP} \ln x_i^{SAP} + v_i - u_i \quad (13)$$

- *No-SAP (without service area population)*

$$\ln(y_i) = \beta_0 + \beta_{seat} \ln x_i^{seat} + \beta_{veh} \ln x_i^{veh} + v_i - u_i \quad (14)$$

Where $y_i, x_i^{seat}, x_i^{SAP} and\ x_i^{veh}$ represent the passenger-kilometer, the number of seats, service area population, vehicle-kilometer of the routes and $\beta$ are unknown parameters to be estimated..

## 5.2 Result of Model 1

a. Cobb-Douglas Function

Table 7: The Result of Cobb-Douglas Function

| Variable/ parameter | Coeff. | | Std. err |
|---|---|---|---|
| $\beta_0$ | -2.134 | * | 0.929 |
| $\beta_{seat}$ | 0.583 | *** | 0.035 |
| $\beta_{SAP}$ | 0.051 | | 0.074 |
| $\beta_{veh}$ | 1.482 | *** | 0.039 |
| $\sigma_u$ | 0.818 | *** | 0.059 |
| $\sigma_v$ | 0.103 | ** | 0.032 |
| $\gamma$ | 0.984 | *** | 0.010 |
| Log likelihood | -81.455 | | |
| Mean technical efficiency | 0.593 | | |
| Observation | 131 | | |

. Indicates parameter Significance at the 10% level
* Indicates Parameter Significance at 5% level
** Indicates Parameter Significance at 1% level
*** Indicates Parameter Significance at 0.1% level

The first analysis investigates the parameters by employing the most fundamental production function, Cobb-Douglas (Battese, George E., and Tim J. Coelli, 1988; Jorgensen, Pedersen, and Volden, 1997). Model 1 applies to the 131 selected routes as shown in Table 6. The "passenger-kilometer" is the dependent variable, while the three independent variables (number of seats, vehicle-kilometer, and service area population) are to be estimated as shown in Equation (8). In this model, an inefficiency error component assumes following the half-normal distribution. Comparing the Cobb-Douglas result to the Translog function is useful to determine which model would be preferable.

SFA estimation using the Cobb Douglas function is displayed in a Table 8, derived from the Equation (8). The first column shows the type of parameters according to the function. The second column displays the coefficient parameters under the Cobb Douglas function. The third column depicts the standard error.

Table 7 shows all the parameters from the explanatory variables $\beta_{seat}, \beta_{SAP}, \beta_{veh}$ indicate a positive effect. The model 1 results finds that parameters (e.g., number of seats, service area population, and vehicle-kilometers) impacts increasing the passenger-kilometer. In other words, expanding the seat-kilometer, vehicle-kilometer, or service area population will proportionally increase the passenger-kilometer. These deductions are sensible according to our expectations. The result supports the finding from the analysis of existing studies.

The estimated error component, as demonstrated by the gamma ($\frac{\sigma_u^2}{\sigma_u^2+\sigma_v^2}$)value is dominated by inefficiency. The error component is widely related to the inefficiency of the bus operation, from the provided services and the passenger output. Table 9 made it clear that the amount of error caused by inefficiency is far more than the amount of error caused by noise

b. Translog Function

The second analysis uses the Translog production function to estimate the Transjakarta sample. The Translog process generates the parameter to apply the relationship between the explanatory variables. According to Albuquerque (1985), the Translog model yields more precise results due to the function's ability to accommodate elasticity among independent variables. Therefore, Translog models are also widely employed to estimate production (cost) function in the transportation field (Ayadi & Hammami, 2015 & Sakai & Shoji, 2010). As a result, the Translog model used in this study is built with "passenger-kilometer" as an dependent variable. In contrast, the three independent variables (the number of seats, vehicle-kilometer, and service area population) are estimated as shown in Equation (9), assuming that the inefficiency error component follows the half-normal distribution. Therefore, this function's result is compared with the previous model (Cobb-Douglas).

Table 8: The parameter estimate of Translog function

| Variable/ parameter | Coeff. | | Std. err |
|---|---|---|---|
| $\beta_0$ | -2.134 | | -10.457 |
| $\beta_{seat}$ | -10.457 | *** | 0.988 |
| $\beta_{SAP}$ | -3.963 | *** | 0.339 |
| $\beta_{veh}$ | 2.754 | *** | 0.193 |
| $\beta_{seat,seat}$ | 4.526 | *** | 0.351 |
| $\beta_{seat,SAP}$ | 0.503 | *** | 0.046 |
| $\beta_{SAP,SAP}$ | 0.208 | *** | 0.026 |
| $\beta_{SAP,veh}$ | -0.213 | *** | 0.022 |
| $\beta_{veh,veh}$ | -0.184 | *** | 0.031 |
| $\beta_{seat,veh}$ | 0.363 | *** | 0.055 |
| $\sigma_u$ | -0.394 | *** | 0.049 |
| $\sigma_v$ | 0.840 | | 0.031 |
| $\gamma$ | 0.000 | | 0.003 |
| Log likelihood | 1.000 | | |
| Mean technical efficiency | -72.606 | | |
| Observation | 0.608 | | |

. Indicates Parameter Significance at the 10% level
* Indicates Parameter Significance at 5% level
** Indicates Parameter Significance at 1% level
*** Indicates Parameter Significance at 0.1% level

The results of the Translog production function is shown in the Table 8. The $\beta_{SAP}$ and $\beta_{veh}$ have a positive effect and are significant at 0.1%. The findings suggest that an increase in the population of service areas and vehicle kilometers can lead to an increase in passenger kilometers. The $\beta_{seat}$ shows a negative effect and significance. That result does not seem reasonable, because increasing the number of seats increases the number of passengers. (the bus capacity will also be able to accommodate more passengers while increasing the passenger-kilometer).

The $\beta_{seat}$ has a positive connection with the passenger-kilometer. At the same time, the estimate of $\beta_{seat,seat}$ is positive and significant. This means that the variable seat shows positive trends when compared to the technical efficiency of services. It is in line with this study's hypothesis that the number of seats increases the technical efficiency.

The $\beta_{seat,SAP}$ coefficient is positive and significant. The study's prediction that the number of seats and service area population will increase the technical efficiency. The coefficient $\beta_{SAP}$ is positive while $\beta_{SAP,SAP}$ has a negative and is significant. These results indicate that the service area population positively increases the passenger-kilometer. And the variable service area population shows negative trends when compared to the technical efficiency of services.

The coefficient $\beta_{SAP,veh}$ has a negative sign; the service area population and vehicle-kilometer have a negative impact on technical efficiency. The coefficient $\beta_{veh}$is positive and significant, implement that increasing vehicle-kilometers are also increasing passenger-kilometers. The $\beta_{veh,veh}$ indicates the positive effect, this means that the variable vehicle-kilometer shows positive trends when compared to the technical efficiency of services. The variable $\beta_{seat,veh}$ indicates the negative effect, which means that the variable seat and vehicle-kilometer showed a negative impact on the passenger- kilometer.

The inefficiency component dominates the error component of the Table 9 function, as indicated by the gamma value of 1. It means that passenger output from the provided services is still far less than the potential. In addition, the noise error component, which represents the natural distraction or error data collection, is less than the inefficiency error component.

c. Comparing Cobb-Douglas and Translog Function

The parameter estimates derived from the Cobb-Douglas and Translog functions have different results. In using the Cobb-Douglas function, each estimated parameter has a positive effect (number of seats, vehicle-kilometer, and service area population). It indicates that an increase in the parameter (input) will also increase the (output) passenger-kilometers. Those results are reasonable; for illustration, the increase in vehicle-kilometers will result in more vehicles that can accommodate more passengers, and the passenger-kilometer will escalate. Another example is that expanding the service area population will increase the bus's service coverage and result in more passengers. Those are due to the service range that accommodates more people.

The particular estimated parameters under the Translog function, excluding the number of seats with negative effect, are also positively shown. Those results are not expected to be reasonable due to the increasing number of seats, which means the service can accommodate more passengers.

Using those estimations, this study concludes that the Cobb-Douglas function is preferable to the Translog function. Those results contradict the claim of Sakai and Shoji (2010), who selected the Translog. Therefore, the results possibly imply that the Cobb-Douglas with fewer parameters is more viable in estimating the Transjakarta sample data than the Translog function. In other words, Cobb-Douglas estimates the data better than Translog does in the case of Transjakarta. It is because translog production function requires more number of data to estimate many parameters, in this case the Cobb Douglass function using the only 3 parameters and trans using the 9 .

## 5.3 Result of Model 2

Table 9: The parameter estimate from model 2

| Variable/ parameter | Cobb-Douglas | |
|---|---|---|
| $\beta_0$ | -0.777 | |
| $\beta_{seat}$ | 0.348 | . |
| $\beta_{SAP}$ | 0.446 | . |
| $\beta_{veh}$ | 1.167 | *** |
| $\sigma_u$ | 0.578 | |
| $\sigma_v$ | 0.246 | |
| $\gamma$ | 0.847 | |
| Log likelihood | -26.374 | |
| Mean technical efficiency | 0.668 | |
| Observation | 49 | |

. Indicates Parameter Significance at the 10% level
* Indicates Parameter Significance at 5% level
** Indicates Parameter Significance at 1% level
*** Indicates Parameter Significance at 0.1% level

After looking into the samples with the Cobb-Douglas and Translog production functions in all routes, the analysis continues by dividing the routes into groups to consider the characteristics of the routes described in Chapter 4. Those groups are classified according to the service characteristic such as the number of seats, route length, and the type of services.

According to the bus size and the seats number, the routes are grouped into two: the large and small bus routes. The large bus routes group includes routes with more than 30 seats (e.g., BRT, non-BRT), while the small bus routes group consists of 11 seats (e.g., minibus). Each route will be examined to evaluate the efficiency regarding several inputs (number of seats, vehicle-kilometer, and service area population) with the passenger-kilometer as an output through model 2 and model 3.

The large-size buses, including the Transjakarta BRT and non-BRT services, operate the bus with more than 30 seats. 12 routes from the BRT services are excluded due to unreliable results. Hence, the analysis of model 2 is only conducted by using 49 routes as described in the Table 5. This observation follows the preceding section's sample data by 131 routes from the entire service. This section only discusses the non-BRT services, which consist of 49 routes. Under this group, the analysis is conducted by utilizing the Cobb-Douglas function as the selected function of model 1. Therefore, the evaluation of each route's efficiency is provided in the final section.

Table 9 demonstrates a large bus routes group's result using the Cobb-Douglas function. The parameter estimates show that the number of seats, the vehicle-kilometers, and the service area population have a positive effect and are significant at different levels. Therefore, those variables (the number of seats, vehicle-kilometer, and the service area population) positively impact the output (passenger-kilometer). Hence, the increasing number of seats, the vehicle-kilometer, or the service area population are also triggering an increase in the number of passenger-kilometer.

*Technical efficiency of Large-size bus route group*

In this section, the non-BRT group measures the efficiency of each route after estimating its parameters in the previous section. These efficiency measurements adhere to the Cobb-Douglas function chosen. Thus, the non-BRT group indicates the lowest and the highest efficiency.

Figure 8: Technical efficiency of large buses routes group

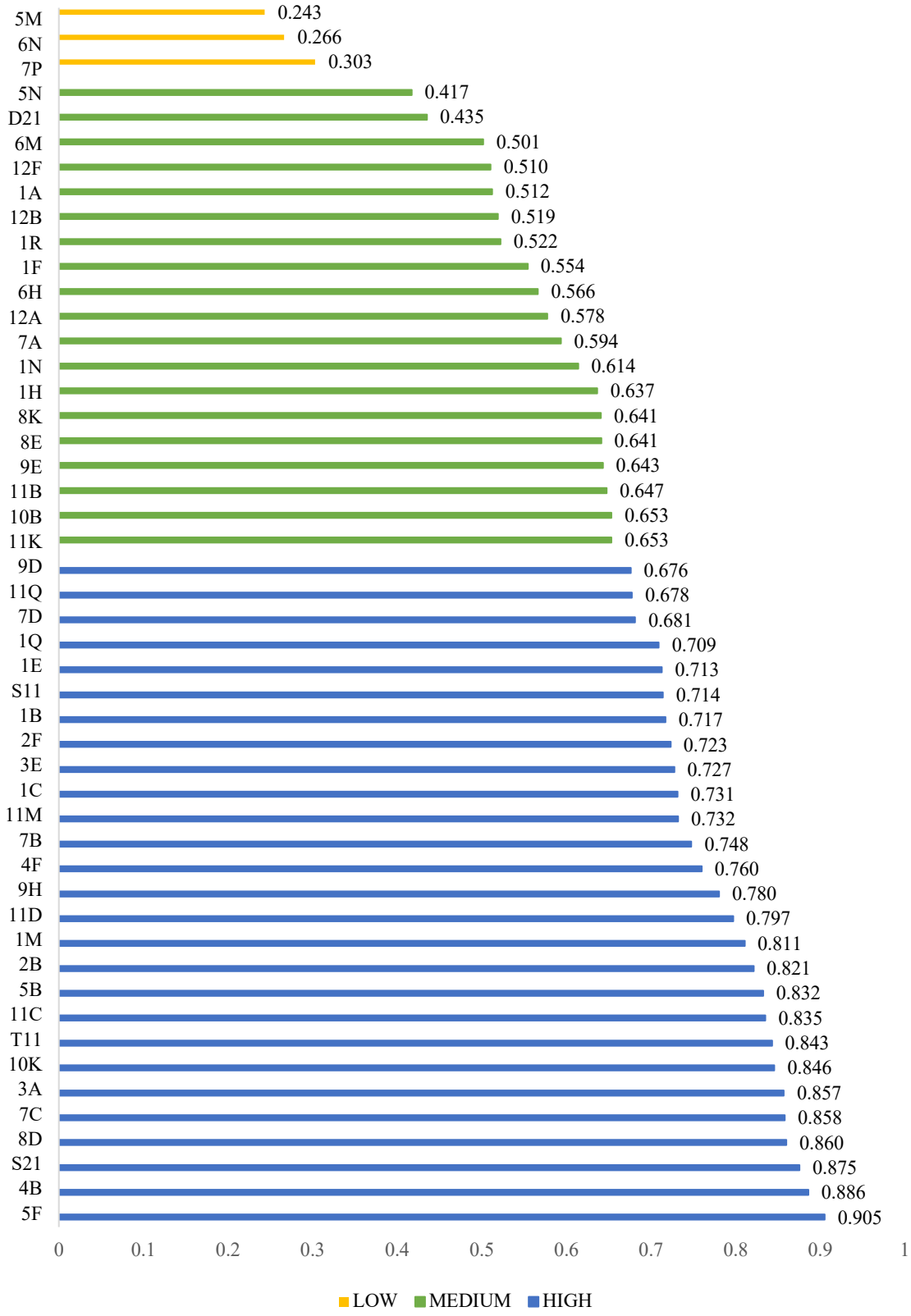


Figure 7 shows the efficiency score from the individual routes from the non-BRT group along the 49 routes. The average efficiency from the non-BRT group is 0.669, with the standard deviation of 0.161 level. As a result, non-BRT routes have efficiency that is not significantly different..

The lowest efficiency route is the "5M" with 0.243 , and the largest value is from the route "5F" with 0.905. Comparing both routes through the data sample indicates that the "5M" has around 3,731,670 number of seat, and 887,698 vehicle-kilometers, with a passenger-kilometer of 77, 411,788,704. Meanwhile, the “5F” has 1,374,705 seats, 284,884 vehicle-kilometers, and a passenger-kilometer of 99,517,159,332. Hence, those indicate that on the passenger-kilometer, routes 5M are less indicated than the routes 5F. The data asserts that the routes "5M" provide more services in terms of seats and vehicle-kilometers, but they accommodate fewer passengers. Inefficient operations are implemented for 5M routes. In another case, the "5F" routes indicate fewer seats and vehicle-kilometers, resulting in more passengers and more efficiency.

Table 10: Technical efficiency group from large buses routes

| SMALL | | MEDIUM | | | | HIGH | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 7P | (0.303) | 11K | (0.653) | 6H | (0.566) | 5F | (0.905) | 2B | (0.821) | 1B | (0.717) |
| 6N | (0.266) | 10B | (0.653) | 1F | (0.554) | 4B | (0.886) | 1M | (0.811) | S11 | (0.714) |
| 5M | (0.243) | 11B | (0.647) | 1R | (0.522) | S21 | (0.875) | 11D | (0.797) | 1E | (0.713) |
| | | 9E | (0.643) | 12B | (0.519) | 8D | (0.860) | 9H | (0.780) | 1Q | (0.709) |
| | | 8E | (0.641) | 1A | (0.512) | 7C | (0.858) | 4F | (0.760) | 7D | (0.681) |
| | | 8K | (0.641) | 12F | (0.510) | 3A | (0.857) | 7B | (0.748) | 11Q | (0.678) |
| | | 1H | (0.637) | 6M | (0.501) | 10K | (0.846) | 11M | (0.732) | 9D | (0.676) |
| | | 1N | (0.614) | D21 | (0.435) | T11 | (0.843) | 1C | (0.731) | | |
| | | 7A | (0.594) | 5N | (0.417) | 11C | (0.835) | 3E | (0.727) | | |
| | | 12A | (0.578) | | | 5B | (0.832) | 2F | (0.723) | | |

Figure 7 shows the efficiency score from the individual routes from the large buses routes group along the 49 routes. The average efficiency of the large buses routes group is 0.669 with a standard deviation of 0.161, and the efficiency result is divided into three ranks. The lowest is from the efficiency value between 0.00-0.33, the medium rank is from > 0.33-0.66, and the largest rank is

from > 0.66 – 1. Form the non-BRT group; the lowest rank consists of three routes, 5M, 6N, and 7P, with efficiency scores of 0.243, 0.66, and 0.303, respectively. Among the lowest rankings, the routes indicate that the number of passenger-kilometer is far lower than the number of provided services from the number of seats and the vehicle-kilometer. Under that condition, the operation is far from efficient due to the input (provide service) being larger than the output (passenger-kilometer). As a consequence, the efficiency value tends to be low.

On the medium rank, 19 routes are consisted, namely 5N, D21, 6M, 12F, 1A, 12B, 1R, 1F, 6H, 12A, 7A, 1N, 1H, 8K, 8E, 9E, 11B, 10B, and 11K with efficiency value from 0.417 to 0.653. Based on the data sample from the medium rank, the output variable as the passenger-kilometer is produced not that far from the input variable as the service provided. The high rank includes 37 routes with an efficiency between 0.676 and 0.905. In such groups with a high-efficiency level, the passenger-kilometer offers huge value compared to the services offered. As a result, most routes, around 75 percent in the non-BRT group, have a high-efficiency level.

## 5.4 Result of Model 3

The small bus routes group is the route that consists of the minibus feeder along the local road in Jakarta. The small bus routes group consist of a bus with 11 number of seats, which is different from large bus routes group. The length of the route is from around 10 km to 40 km. This research observation the sample data from the previous section, 131 routes. This part will specifically focus on the minibus services, consisting of only 70 routes. The analysis will be conducted using the Cobb-Douglas production function.

Table 11: Multicolonearity test result

| Predictor variable | VIF |
|---|---|
| Vehicle-kilometer | 9.711 |
| Number of seats | 7.957 |
| Service area population | 4.127 |

In this group, the Cobb-Douglas functions to estimate the parameter from the output (passenger-kilometer) with the input variable (number of seats, vehicle-kilometer, and the service area population). The result from that estimation detects the "multicollinearity" from the independent variables, as shown in the Table 11. Hence, the reason for vehicle-kilometer and the number of seat variables have the Variance Inflation Factor (VIF) by more than five and the service population by four as the medium multicollinearity. Consequently, the analysis continues to exclude the part of the input variable to prevent multicollinearity. The model consists of three models that exclude the particular input variable from three variables which are the number of seats, vehicle-kilometers, and service area population. The first model is "**No. Veh**" which excludes the vehicle-kilometer, "**No. Seat**" excludes the number of seats, and the "**No. Sap**" excludes the service area population among the input variable as shown in the Equation (11).

Table 13 demonstrates the result from the three models **no. veh, no. sap**, and **no. seat** using the Cobb-Douglas function. The three models' results show that the number of seats, vehicle-kilometers, and the service area population has a positive effect and are significant in the model with these variables. Therefore, those implemented variables (the number of seats, vehicle-kilometers, and the service area population) positively impact the output (passenger-kilometer). Hence, the increasing number of seats, the vehicle-kilometer, or the service area population also increase passenger-kilometers.

From the gamma value close to one, we can note that the error component is dominated by the inefficiency component rather than the noise. Among the three models, the "no veh" model is selected as the best fit model because it shows acceptable degree of significant for all parameters.

Table 12: The Result of Cobb-Douglas Function in Model 3

| **Variable/ parameter** | **No. Veh** | | **Std. err** | **No. Seat** | | **Std. err** | **No. Sap** | | **Std. err** |
|---|---|---|---|---|---|---|---|---|---|
| $\beta_0$ | -26.720 | *** | 3.583 | -4.937 | | 3.441 | -4.424 | ** | 1.619 |
| $\beta_{seat}$ | 2.262 | *** | 0.104 | | | | 0.593 | *** | 0.157 |
| $\beta_{SAP}$ | 1.668 | *** | 0.180 | -0.593 | *** | 0.155 | | | |
| $\beta_{veh}$ | | | | 2.262 | *** | 0.106 | 1.668 | *** | 0.181 |
| $\sigma_u$ | 0.385 | * | 0.189 | 0.385 | | 0.188 | 0.385 | | 0.191 |
| $\sigma_v$ | 0.243 | * | 0.094 | 0.243 | * | 0.096 | 0.243 | *** | 0.096 |
| $\gamma$ | 0.714 | * | 0.352 | 0.714 | | 0.356 | 0.714 | | 0.357 |
| Log-likelihood | -22.293 | | | -22.293 | | | -22.293 | | |
| Mean technical efficiency | 0.756 | | | 0.756 | | | 0.756 | | |
| Observation | 70 | | | 70 | | | 70 | | |

. Indicates Parameter Significance at the 10% level
* Indicates Parameter Significance at 5% level
** Indicates Parameter Significance at 1% level
*** Indicates Parameter Significance at 0.1% level

*Technical efficiency small bus routes group*

Each efficiency analysis is conducted using the Cobb-Douglas with "no. veh" as the selected model function from the input variable (number of seats, service area population) with the passenger-kilometer as the output variable. The average efficiency of the small bus routes group is 0.757, with a standard deviation of 0.107. Consequently, they infer that most minibus routes have a high-efficiency level– each route has slightly varying levels of efficiency.

The lowest efficiency route is the "JAK.10A" by 0.297, and the largest value is from the route "JAK.08" by 0.23. Comparing both routes through the data sample indicates that the "JAK.10A" has around 131,043 number of seat, and 137,000 vehicle-kilometers, with a passenger-kilometer of 864,603,845. While the "JAK.08" has 287,012 seats and 414,865 vehicle-kilometers with a passenger-kilometer of 82,082,365,806. Hence, those indicate that on the passenger-kilometer,

the routes "JAK.10A" indicate less than the routes "JAK.08". Those data assert that the routes "JAK.10A" provide more service in terms of seats and vehicle-kilometers, but they accommodate fewer passengers. Those are implemented in inefficient operations. In another case, the "JAK.08" routes indicate fewer seats and vehicle-kilometers, resulting in more passengers and more efficiency.

The result is divided into three levels of efficiency which are low (1-3.33), medium (< 3.33- 6.66), and highest (< 6.66 -1). Regarding passenger-kilometers, the JAK.10A routes are the only ones operating at a low level. These routes produce relatively fewer passenger-kilometers, according to the data. Regarding those conditions, the efficiency result is at a low level of 0.297.

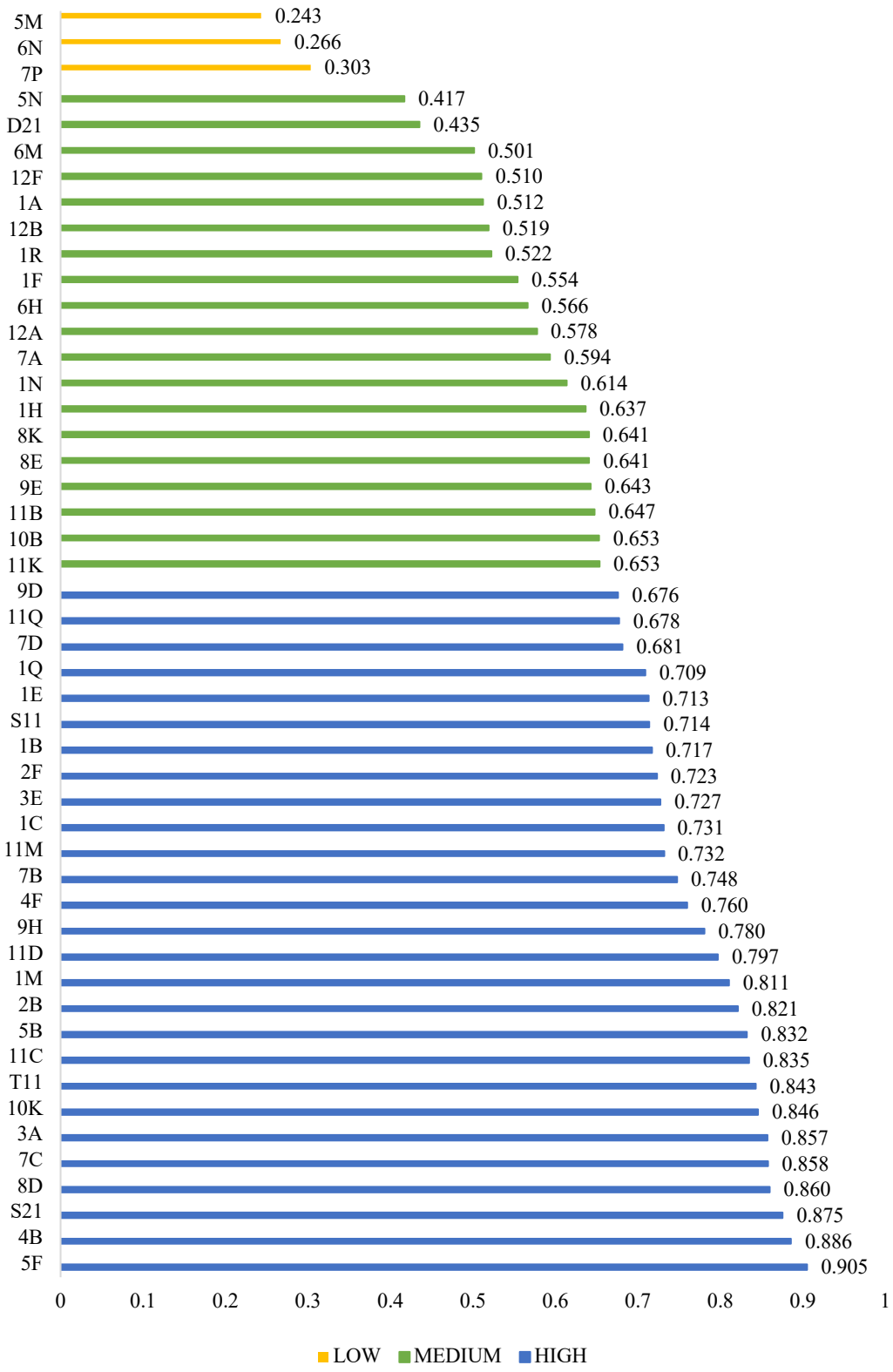
The medium rank of the efficiency includes 19 routes among 70 routes with an average efficiency of 0.62. the lowest number is 0.526, and the highest is 0.659, by the routes JAK. 10. Those medium routes are shown in the Table 14, and according to the observation data, the number of seats, vehicle-kilometer, and service area population result in a reasonable output of passenger-kilometer.

Moreover, the last rank is the large rank which includes 57 routes from 70 routes. Indicated by around 80 percent, the small-size bus has a good enough efficiency. The average of this group is 0.79. Those results signify that in this group, each route results in high passenger-kilometers from the provided services. Hence, the service provision from the number of seats, vehicle-kilometers, and service area population is qualified to produce appropriate passenger-kilometers.

Table 13: Technical efficiency small bus routes group

| HIGH | | | | MEDIUM | | LOW | |
|---|---|---|---|---|---|---|---|
| JAK.08 | (0.923) | JAK.25 | (0.841) | JAK.10 | (0.659) | JAK.10A | (0.297) |
| JAK.09 | (0.919) | JAK.01 | (0.841) | JAK.35 | (0.659) | | |
| JAK.03 | (0.897) | JAK.20 | (0.832) | JAK.33 | (0.654) | | |
| JAK.45 | (0.882) | JAK.44 | (0.827) | JAK.71 | (0.650) | | |
| JAK.38 | (0.881) | JAK.47 | (0.825) | JAK.41 | (0.648) | | |
| JAK.43 | (0.870) | JAK.61 | (0.823) | JAK.80 | (0.646) | | |
| JAK.54 | (0.868) | JAK.64 | (0.823) | JAK.10B | (0.631) | | |
| JAK.72 | (0.867) | JAK.34 | (0.822) | JAK.74 | (0.624) | | |
| JAK.28 | (0.865) | JAK.26 | (0.820) | JAK.13 | (0.607) | | |
| JAK.59 | (0.864) | JAK.60 | (0.820) | JAK.16 | (0.583) | | |
| JAK.14 | (0.853) | JAK.18 | (0.818) | JAK.112 | (0.559) | | |
| JAK.06 | (0.851) | JAK.05 | (0.817) | JAK.85 | (0.526) | | |
| JAK.36 | (0.850) | JAK.21 | (0.815) | | | | |
| JAK.07 | (0.846) | JAK.51 | (0.811) | | | | |
| JAK.58 | (0.842) | JAK.02 | (0.811) | | | | |
| JAK.29 | (0.803) | JAK.22 | (0.716) | | | | |
| JAK.12 | (0.800) | JAK.04 | (0.715) | | | | |
| JAK.31 | (0.799) | JAK.30 | (0.715) | | | | |
| JAK.24 | (0.797) | JAK.37 | (0.706) | | | | |
| JAK.11 | (0.793) | JAK.52 | (0.697) | | | | |
| JAK.75 | (0.789) | JAK.40 | (0.692) | | | | |
| JAK.50 | (0.778) | JAK.117 | (0.690) | | | | |
| JAK.73 | (0.773) | JAK.53 | (0.683) | | | | |
| JAK.56 | (0.751) | JAK.84 | (0.679) | | | | |
| JAK.49 | (0.750) | JAK.15 | (0.678) | | | | |
| JAK.19 | (0.735) | JAK.27 | (0.676) | | | | |
| JAK.77 | (0.732) | JAK.17 | (0.674) | | | | |
| JAK.42 | (0.732) | | | | | | |
| JAK.46 | (0.720) | | | | | | |
| JAK.39 | (0.717) | | | | | | |

Figure 9: Technical efficiency of small bus routes group



*Technical efficiency comparison between the group*

Table 14: Statistic summary of technical efficiency in buses routes group

| | Large bus routes | Small bus routes |
|---|---|---|
| Mean | 0.669 | 0.757 |
| Median | 0.681 | 0.791 |
| Minimum | 0.243 | 0.297 |
| Maximum | 0.905 | 0.923 |
| Coefficienct of Variation (Cov) | 0.24 | 0.141 |
| N | 49 | 70 |

Table 15 compares technical efficiency between the large bus route group and small bus route group in Transjakarta case. The services in the small bus route group is likely able to accommodate more passengers than large bus routes group. It also reveals that small bus route group has lower efficiency. It is in line with the previous analysis that shows the passenger bus efficiency is determined by the number of seats, vehicle-kilometers, and service area population at a certain point. Alternatively, it means that a better efficiency can be achieved if provided services meet the appropriate number of passengers.

The average technical efficiency of the small-size bus is higher than the large-size bus, around 0.2 and 0.9. Even though the minimum and the maximum technical efficiency from both groups have around the same number, there is still a gap in the efficiency between the routes among the group.

# CHAPTER 6. CONCLUSION

## 6.1 The Main Results and Limitations

Alongside the operation, Transjakarta collaborates with other modes of public transit authority, a financial company, and the IT Providers to offer enhanced passenger services. A wide range of services, including the double bus, minibus, service of free pickup for the disabled, and woman-only buses, are available to provide an inclusive service for the entire population. In order to avoid traffic jams in the city's core, BRT service with priority lane services has been implemented to provide the fastest service possible. The cooperative payment with "Jaklingko" provides an integrated fare payment for all public transport in Jakarta. However, when operating the services, evaluations are always necessary to determine how well the services satisfy the need and how they might be improved.

This research aimed at determining the best production function and assess the level of technical efficiency exhibited by Jakarta's public buses (Transjakarta) on various routes. The application of Cobb-Douglas function gave rise to plausible results than those of the Translog production function. It sees that Translog production function is not appropriate to use because the Transjakarta can only provide limited set of data. They have not provide time-series data for multiple years. To use the Translog production function in SFA, there should be more data sets. The research also finds that the efficiency of the whole small-size bus routes is slightly larger than the large-size bus routes.

This study provided a clear illustration of the SFA application as the econometric method for evaluating the service efficiency of Transjakarta in Indonesia. According to our studies, the Cobb-Douglas function produces more stable SFA model than the Translog function. Unexpectedly, this study is in contrast with the findings of Sakai and Shoji (2010) based on 525 observations of the cost function of subsidies and contracts in Japan. Consequently, our research provides insight into the SFA production function applied to a small sample in a developing country. However, the results – which was obtained from a limited number of data – generate a question of whether

or not the answer would be the same if the research was conducted in developing countries which have a large number of data observations.

## 6.2 The Future Research

Based on the conclusion, practitioners should consider the availability of data to acquire reliable results. For this empirical study, time series data is more appropriate for generating a reliable result. Moreover, the observation sample is considerable in the analysis due to the type of the production function of Stochastic Frontier Analysis (SFA).

In addition, future research needs to evaluate the variable selection criteria based on the research objectives. In this study, the addition of the cost variable can provide a deeper understanding of how to evaluate efficiency.

Policy makers should consider the adjustment to the bus size regarding the attraction place and area population. Those considerations could be implemented to operate the appropriate bus size that meets the demand for bus service and increases the bus services' efficiencies.

However, the evaluation of the provision of public services, particularly transportation, remains a challenge in developing countries. The challenge emerged due to the access restriction of the administrative data required. Hence, by evaluating limited data, this research contributes to improving public service delivery. This work contributes to the study of frontier analysis in a developing country case

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# Appendices

**Appendix 1. Transjakarta routes that were not considered in the analysis**

| ROUTE | SERVICE TYPE | NOTE |
|---|---|---|
| 10C | NON-BRT | ROUTE REVITALIZATION |
| 10H | NON-BRT | ROUTE REVITALIZATION |
| 10D | NON-BRT | ROUTE REVITALIZATION |
| 11A | NON-BRT | ROUTE REVITALIZATION |
| 11R | NON-BRT | ROUTE REVITALIZATION |
| 11T | NON-BRT | ROUTE REVITALIZATION |
| 11U | NON-BRT | ROUTE REVITALIZATION |
| 11V | NON-BRT | ROUTE REVITALIZATION |
| 12E | NON-BRT | ROUTE REVITALIZATION |
| 12K | NON-BRT | ROUTE REVITALIZATION |
| 12M | NON-BRT | ROUTE REVITALIZATION |
| 13A | NON-BRT | ROUTE REVITALIZATION |
| 13C | NON-BRT | ROUTE REVITALIZATION |
| 13D | NON-BRT | ROUTE REVITALIZATION |
| 13E | NON-BRT | ROUTE REVITALIZATION |
| 13F | NON-BRT | ROUTE REVITALIZATION |
| 14 | NON-BRT | ROUTE REVITALIZATION |
| 1T | ROYAL TRANS | UNAVAILABLE DATA |
| 1U | ROYAL TRANS | UNAVAILABLE DATA |
| 2D | NON-BRT | ROUTE REVITALIZATION |
| 2E | NON-BRT | ROUTE REVITALIZATION |
| 2K | NON-BRT | ROUTE REVITALIZATION |
| 2A | NON-BRT | ROUTE REVITALIZATION |
| 3B | NON-BRT | ROUTE REVITALIZATION |
| 3C | NON-BRT | ROUTE REVITALIZATION |
| 3D | NON-BRT | ROUTE REVITALIZATION |
| 3X | NON-BRT | ROUTE REVITALIZATION |
| 3F | NON-BRT | ROUTE REVITALIZATION |
| 4A | NON-BRT | ROUTE REVITALIZATION |
| 4H | NON-BRT | ROUTE REVITALIZATION |
| 4K | NON-BRT | ROUTE REVITALIZATION |
| 4M | NON-BRT | ROUTE REVITALIZATION |
| 4C | NON-BRT | ROUTE REVITALIZATION |
| 4D | NON-BRT | ROUTE REVITALIZATION |
| 5A | NON-BRT | ROUTE REVITALIZATION |
| 5E | NON-BRT | ROUTE REVITALIZATION |
| 5Y | NON-BRT | ROUTE REVITALIZATION |
| 5K | NON-BRT | ROUTE REVITALIZATION |
| 5C | NON-BRT | ROUTE REVITALIZATION |
| 5D | NON-BRT | ROUTE REVITALIZATION |

| | | |
|---|---|---|
| 6E | NON-BRT | ROUTE REVITALIZATION |
| 6F | NON-BRT | ROUTE REVITALIZATION |
| 6R | NON-BRT | ROUTE REVITALIZATION |
| 6A | NON-BRT | ROUTE REVITALIZATION |
| 6B | NON-BRT | ROUTE REVITALIZATION |
| 6D | NON-BRT | ROUTE REVITALIZATION |
| 6Q | NON-BRT | ROUTE REVITALIZATION |
| 7E | NON-BRT | ROUTE REVITALIZATION |
| 7M | NON-BRT | ROUTE REVITALIZATION |
| 7N | NON-BRT | ROUTE REVITALIZATION |
| 7F | NON-BRT | ROUTE REVITALIZATION |
| 8C | NON-BRT | ROUTE REVITALIZATION |
| 8F | NON-BRT | ROUTE REVITALIZATION |
| 8A | NON-BRT | ROUTE REVITALIZATION |
| 9B | NON-BRT | ROUTE REVITALIZATION |
| 9K | NON-BRT | ROUTE REVITALIZATION |
| 9M | NON-BRT | ROUTE REVITALIZATION |
| 9A | NON-BRT | ROUTE REVITALIZATION |
| 9C | NON-BRT | ROUTE REVITALIZATION |
| B15 | COUNTY FEEDER | UNAVAILABLE DATA |
| B16 | COUNTY FEEDER | UNAVAILABLE DATA |
| B23 | COUNTY FEEDER | UNAVAILABLE DATA |
| B24 | COUNTY FEEDER | UNAVAILABLE DATA |
| D11 | COUNTY FEEDER | UNAVAILABLE DATA |
| D31 | COUNTY FEEDER | UNAVAILABLE DATA |
| DA1 | COUNTY FEEDER | UNAVAILABLE DATA |
| DA2 | COUNTY FEEDER | UNAVAILABLE DATA |
| DA3 | COUNTY FEEDER | UNAVAILABLE DATA |
| DA4 | COUNTY FEEDER | UNAVAILABLE DATA |
| GR1 | FREE SERVICE | UNAVAILABLE DATA |
| GR2 | FREE SERVICE | UNAVAILABLE DATA |
| GR3 | FREE SERVICE | UNAVAILABLE DATA |
| GR4 | FREE SERVICE | UNAVAILABLE DATA |
| GR5 | FREE SERVICE | UNAVAILABLE DATA |
| JAK88 | MICROTRANS | UNCOMPLETE DATA |
| S22 | COUNTY FEEDER | UNAVAILABLE DATA |
| S23 | COUNTY FEEDER | UNAVAILABLE DATA |
| S41 | COUNTY FEEDER | UNAVAILABLE DATA |
| JIS3 | SPECIAL FEEDER | UNAVAILABLE DATA |
| TRS1 | BORDERLINE FEEEDER | UNAVAILABLE DATA |
| TRS2 | BORDERLINE FEEEDER | UNAVAILABLE DATA |
| TRS3 | BORDERLINE FEEEDER | UNAVAILABLE DATA |
| TRS4 | BORDERLINE FEEEDER | UNAVAILABLE DATA |
| TRS5 | BORDERLINE FEEEDER | UNAVAILABLE DATA |
| TRS6 | BORDERLINE FEEEDER | UNAVAILABLE DATA |

| | | |
|---|---|---|
| TRS7 | BORDERLINE FEEEDER | UNAVAILABLE DATA |
| TRS8 | BORDERLINE FEEEDER | UNAVAILABLE DATA |
| TRS9 | BORDERLINE FEEEDER | UNAVAILABLE DATA |
| TRS14 | BORDERLINE FEEEDER | UNAVAILABLE DATA |
| EV1 | ELECTRIC VEHICLE | UNAVAILABLE DATA |
| BW1 | TOUR SERVICE | UNAVAILABLE DATA |
| BW2 | TOUR SERVICE | UNAVAILABLE DATA |
| BW3 | TOUR SERVICE | UNAVAILABLE DATA |
| BW4 | TOUR SERVICE | UNAVAILABLE DATA |
| BW5 | TOUR SERVICE | UNAVAILABLE DATA |
| BW6 | TOUR SERVICE | UNAVAILABLE DATA |
| BW7 | TOUR SERVICE | UNAVAILABLE DATA |
| L10A | COUNTY FEEDER | UNAVAILABLE DATA |
| L10B | COUNTY FEEDER | UNAVAILABLE DATA |
| MR1 | MRT FEEDER | UNAVAILABLE DATA |
| MR2 | MRT FEEDER | UNAVAILABLE DATA |
| MR3 | MRT FEEDER | UNAVAILABLE DATA |
| MR5 | MRT FEEDER | UNAVAILABLE DATA |
| MR8 | MRT FEEDER | UNAVAILABLE DATA |
| MR9 | MRT FEEDER | UNAVAILABLE DATA |
| T12 | COUNTY FEEDER | UNAVAILABLE DATA |
| 10A | NON-BRT | ROUTE REVITALIZATION |
| 10B | NON-BRT | ROUTE REVITALIZATION |
| 10C | NON-BRT | ROUTE REVITALIZATION |
| 10D | NON-BRT | ROUTE REVITALIZATION |
| 10H | NON-BRT | ROUTE REVITALIZATION |
| 10K | NON-BRT | ROUTE REVITALIZATION |

**Appendix 2. Applied coding**

```
#131 routes cobb douglass and translog
library(frontier)
library(readxl)
alldeletenoldelete <- read_excel("alldeletenoldelete.xlsx")
alldeletenoldelete <- as.data.frame(alldeletenoldelete)
alldeletenoldelete

cbbnoldeletenoldelete <- sfa(log(pass) ~ log(seat) + log(sap)+log(veh),
                        data = alldeletenoldelete)
summary(cbbnoldeletenoldelete, extraPar = TRUE)
efficiencies(cbbnoldeletenoldelete)

transdel131 <- sfa( log(pass) ~ log(seat) + log(sap)+log(veh)+
                 I(0.5 * log(seat)^2) + I(log(seat) * log(sap))+I(0.5*log(sap)^2) +
                 I(log(sap)*log(veh))+I(0.5 * log(veh)^2) + I(log(seat)*log(veh)),
               data = alldeletenoldelete)
summary( transdel131, extraPar = TRUE )
efficiencies(transdel131)

lrtest(cbbnoldeletenoldelete, transdel131)

library(frontier)
library(readxl)
brt1 <- read_excel("brt.xlsx")
brt1 <- as.data.frame(brt1)
brt1

cbbbrt1 <- sfa(log(pass) ~ log(seat) + log(sap)+log(veh),
              data = brt1)
summary(cbbbrt1, extraPar = TRUE)

cbbbrt2 <- sfa(log(pass) ~ log(seat)+log(veh),
            data = brt1)
summary(cbbbrt2, extraPar = TRUE)

cbbbrt3 <- sfa(log(pass) ~ log(seat) + log(sap),
            data = brt1)
summary(cbbbrt3, extraPar = TRUE)


#translog
transbrt1 <- sfa( log(pass) ~ log(seat) + log(sap)+log(veh)+
                 I(0.5 * log(seat)^2) + I(log(seat) * log(sap))+I(0.5*log(sap)^2) +
                 I(log(sap)*log(veh))+I(0.5 * log(veh)^2) + I(log(seat)*log(veh)),
               data = brt1)
summary( transbrt1, extraPar = TRUE )
library(frontier)
library(readxl)
minibus1 <- read_excel("minibus.xlsx")
minibus1 <- as.data.frame(minibus1)
```

```
minibus1

cbbminibus1 <- sfa(log(pass) ~ log(seat) + log(sap)+log(veh),
            data = minibus1)
summary(cbbminibus1)

cbbminibus22 <- sfa(log(pass) ~ log(seat) + log(sap),
                data = minibus1)
summary(cbbminibus22, extraPar = TRUE )
efficiencies(cbbminibus22)

cbbminibusnoseat <- sfa(log(pass) ~ log(sap)+log(veh),
                data = minibus1)
summary(cbbminibusnoseat, extraPar = TRUE)
efficiencies(cbbminibusnoseat)

cbbminibusnosap <- sfa(log(pass) ~ log(seat) +log(veh),
                data = minibus1)
summary(cbbminibusnosap, extraPar = TRUE )
efficiencies(cbbminibusnosap)

#LR test
lrtest(cbbminibus22,transminibus22)


#translog
transminibus1 <- sfa( log(pass) ~ log(seat) + log(sap)+log(veh)+
                I(0.5 * log(seat)^2) + I(log(seat) * log(sap))+I(0.5*log(sap)^2) +
                I(log(sap)*log(veh))+I(0.5 * log(veh)^2) + I(log(seat)*log(veh)),
               data = minibus1)
summary( transminibus1, extraPar = TRUE )

transminibus22 <- sfa( log(pass) ~ log(seat) + log(sap)+
                  I(0.5 * log(seat)^2) + I(log(seat) * log(sap))+I(0.5*log(sap)^2),
                 data = minibus1)
summary( transminibus22, extraPar = TRUE )
efficiencies(transminibus22)

transminibusosap <- sfa( log(pass) ~ log(seat) +log(veh)+
                  I(0.5 * log(seat)^2) +I(0.5 * log(veh)^2) + I(log(seat)*log(veh)),
                 data = minibus1)
summary( transminibusosap, extraPar = TRUE )
efficiencies(transminibusosap)

transminibusnoseat <- sfa( log(pass) ~ log(sap)+log(veh)+ I(0.5*log(sap)^2) +
                  I(log(sap)*log(veh))+I(0.5 * log(veh)^2),
                 data = minibus1)
summary( transminibusnoseat, extraPar = TRUE )
efficiencies(transminibusnoseat)
```

```
#translod covariants
library(frontier)
library(readxl)
minibuswithco <- read_excel("minibuswithco.xlsx")
minibus1 <- as.data.frame(minibus1)
minibus1

transminibus22 <- sfa( log(pass) ~ log(seat) + log(sap)+
                    I(0.5 * log(seat)^2) + I(log(seat) * log(sap))+I(0.5*log(sap)^2),
                  data = minibus1)
summary( transminibus22, extraPar = TRUE )
efficiencies(transminibus22)


minitranseffco <- sfa( log(pass) ~ log(seat) + log(sap)+
                    I(0.5 * log(seat)^2) + I(log(seat) * log(sap))+I(0.5*log(sap)^2),
                  data = minibus1)


library(frontier)
library(readxl)
nonbrt1 <- read_excel("nonbrt.xlsx")
nonbrt1 <- as.data.frame(nonbrt1)
nonbrt1

cbbnonbrt1 <- sfa(log(pass) ~ log(seat) + log(sap)+log(veh),
                data = nonbrt1)
summary(cbbnonbrt1, extraPar = TRUE)
efficiencies(cbbnonbrt1)


#translog
transnonbrt1 <- sfa( log(pass) ~ log(seat) + log(sap)+log(veh)+
                    I(0.5 * log(seat)^2) + I(log(seat) * log(sap))+I(0.5*log(sap)^2) +
                    I(log(sap)*log(veh))+I(0.5 * log(veh)^2) + I(log(seat)*log(veh)),
                  data = nonbrt1)
summary( transnonbrt1, extraPar = TRUE )


library(frontier)
library(readxl)
nonbrtwithco <- read_excel("nonbrtwithco.xlsx")
nonbrtwithco <- as.data.frame(nonbrtwithco)
nonbrtwithco

cbbnonwithco1 <- sfa(log(pass) ~ log(seat) + log(sap)+log(veh)| dm,
                data = nonbrtwithco)
summary(cbbnonwithco1, extraPar = TRUE)

cbbnonwithco2 <- sfa(log(pass) ~ log(seat) + log(sap)+log(veh)| dm + crss,
                data = nonbrtwithco)
summary(cbbnonwithco2, extraPar = TRUE)
```

```
cbbnonwithco3 <- sfa(log(pass) ~ log(seat) + log(sap)+log(veh)| acdt + crss + dm,
                 data = nonbrtwithco)
summary(cbbnonwithco3, extraPar = TRUE)

library(frontier)
library(readxl)
minibus1 <- read_excel("minibus.xlsx")
minibus1 <- as.data.frame(minibus1)
minibus1

head(minibus1)
model234 <- lm (pass ~ veh + seat + sap, data = minibus1)
summary(model234)

library(car)
vif(model234)

vif_values <- vif(model234)
barplot(vif_values, main = "VIF Values", horiz = TRUE, col = "steelblue")
abline(v = 5, lwd = 3, lty = 2)
```

# Abstract in Korean

본 논문은 버스노선의 효율성 분석을 목적으로 한다. 이를위해 자카르타의 공공버스 운영회사 (Transjakarta)에서 운행하는 131 개 버스노선의 승객수, 버스댓수 등의 통계를 수집하였다. 효율성 분석은 계량경제 모델 중 하나인 Stochastic Frontier Analysis (SFA)방법을 이용하였다. 특히 대표적이 비용한수인 트랜슬로그 (Translog) 와 Cobb-Douglas 함수중 어떤 함수가 자카르다 버스 효율성 분석에 적절한지 비교한다. 산출 변수는 승객, Km 이고 차량 Km, 버스 용량 및 서비스 지역 인구등이 입력 변수로 설정하였다. 연구 결과 Cobb-Douglas 비용 함수가 트랜슬로그 (Translog) 비용한수를 사용 보다 더 좋은 효율성 평가 모델을 도출하는 것으로 나타났다. 본 연구에서 좌석 수, 차량 Km 및 서비스 지역 인구는 승객 Km 와 양의 상관 관계가 있다는 것을 밝혔다. 그 결과, 소그룹과 대그룹 모두 최소 효율 약 0.2, 최대 효율 약 0.9 로 나타나 버스노선 간 효율 차이가 큰 것으로 나타났다. 가장 낮은 효율이 제공되는 서비스(차량 주행 거리, 좌석 수)가 차량에 대한 수요보다 크다는 것을 보여준다.

키워드 : 평가, 효율성, 버스노선, Stochastic Frontier Analysis (SFA), 생산함수

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