A VIABLE MULTI-CRITERIA GREEN FLEET PLANNING FOR ELECTRIC BUS OPERATIONS

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A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Science (Honours) Applied Mathematics with Computing

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DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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APPROVAL FOR SUBMISSION

I certify that this project report entitled **"A VIABLE MULTI-CRITERIA GREEN FLEET PLANNING FOR ELECTRIC BUS OPERATIONS"** was prepared by **WONG SHONG XUAN** has met the required standard for submission in partial fulfilment of the requirements for the award of Bachelor of Science (Honours) Applied Mathematics with Computing at Universiti Tunku Abdul Rahman.

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ABSTRACT

Recognizing that electric bus is a primary key in decarbonization, and also understandable that the biggest obstacle to operating electric buses is its lifetime total expenses, thus electric bus operations require a proper-designed planning as numerous influential factors (e.g., bus frequency, bus quantity, passenger load factor, etc.) would significantly affecting the bus performance. With the aid of the Fuzzy TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), the project identifies the most suitable bus routes for electrification by integrating environmental and economic considerations, as well as devising a heterogeneous electric bus plan to support the operational system. In the illustrative case study for Universiti Tunku Abdul Rahman (UTAR), Sungai Long campus, Route-1, which covers the Bandar Sungai Long & Palm Walk (Morning Route), is identified as the most suitable route for BEB operations. For this route, the Pelican Yutong e9 BEB is deemed the most favourable for replacing conventional buses (CB)s with passenger loads of less than 22, and two of these buses are recommended for passenger loads exceeding 33. For passenger loads between 22 and 33, the BYD eBus 13 is recommended to replace conventional buses. In a nutshell, this project used Fuzzy TOPSIS to identify the most suitable bus routes and favourable bus types for bus electrification while considering environmental and economic factors. Its contribution spans the environmental and transportation sectors, supporting sustainable transit solutions.

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a_{rj}^{p}	first element in fuzzy number
A^{+}	fuzzy positive ideal solution (FPIS)
A^{-}	fuzzy negative ideal solution (FNIS)
a	frontal area of BEB
AER	all-electric range
$AVKD$	annual vehicle-kilometres of demand
$AVKT$	annual vehicle-kilometres travelled
b_{rj}^{p}	second element in fuzzy number
B_{size}	battery size
BC_{new}	cost of a new battery
BC_{old}	cost of an old battery
c_{rj}^{p}	third element in fuzzy number
C_d	drag coefficient of BEB frontal cross-sectional area
C_E	energy cost
C_I	insurance cost
C_j	criterion
C_M	maintenance and repair cost
C_N	implicit cost
C_r	coefficient of rolling resistance
C_T	taxes and fees
C_V	vehicle cost
CC_r	closeness coefficient
$CVKT$	cumulative vehicle-kilometres-travelled
d_{00}	route length covered in acceleration
d_{01}	route length covered in constant velocity
d_{02}	route length covered in deceleration
d	route length covered
d_c	whole bus route length
d_i^{+}	distance from each bus route r to FPIS
d_i^{-}	distance from each bus route r to FNIS

$d(\tilde{v}_{rj}, \tilde{v}_j^+)$	distance between each criterion j to the FPIS
$d(\tilde{v}_{rj}, \tilde{v}_j^-)$	distance between each criterion j to the FNIS
dr	discount rate
D_{rj}^p	decision-making matrix with $\tilde{x}_{rj}^p$
DC_E	daily energy cost
DC_I	daily insurance cost
DC_M	daily maintenance and repair cost
DC_N	daily implicit cost
DC_T	daily taxes and fees
DC_V	daily vehicle cost
$DPCO^{y,r}$	daily perceived cost of ownership with bus type y and bus route r
$DVKD$	daily vehicle-kilometres demand
$DVKT$	daily vehicle-kilometres travelled
e	estimated DVKT on highway
EC	electricity consumption rate
E_0	mechanical energy at the wheels at constant speed
E_{a-}	mechanical energy at the wheels in deceleration
E_{a+}	mechanical energy at the wheels in acceleration
E_{aux}	auxiliary energy
$E_{CO_2}^{y,r}$	CO_2 emissions with bus type y and bus route r
$E_{cons}^{y,r}$	energy consumption with bus type y and bus route r
EC_{kg}	electricity consumption rate per kg
E_{loss}	energy loss in charging station
E_{mec}	mechanical energy
f	bus frequency
F_E	annual cost of electricity of a BEB
FC	fuel consumption rate
g	gravity
G	highway tolls fare
I	electricity current
I_A	passenger accident insurance

I_D	car damage insurance
I_L	liability insurance
I_S	supplementary liability insurance
j	influential factor
k	density of air
L	total ownership time
LC	labour cost
lf	passenger load factor
mc	maintenance cost ratio
m_{BEB}	mass of empty BEB
m_f	fictive mass of rolling inertia
m_p	passenger weight
M	maintenance expenditure
$\tilde{n}_{rj}$	normalized aggregated fuzzy number
n	number of passenger seats
N_A	alternative vehicle cost
N_R	range anxiety cost
N_{RA}	repower annoyance cost
$\widetilde{N}$	normalized fuzzy decision-making matrix with $\tilde{n}_{rj}$
OP	annual operating days
p	decision maker
P	purchase cost
PF	cumulative probability distribution function of adopting the alternative vehicle
PR_S	charging powers for slow charging
PR_F	charging powers for fast charging
$PR_{(z)}$	charging powers respective to charging strategy z
P_{aux}	auxiliary power
P_c	copper loss
P_{cable}	transmission cable loss
P_d	dielectric loss
P_e	eddy current loss
P_E	electricity price

P_F	fuel price
P_h	hysteresis loss
P_J	joule effect loss
P_{loss}	power loss in the power supply system
P_{ped}	power electronic device loss
P_s	stand-by loss
P_{S-F}	service fees for fast charging
P_{S-S}	service fees for slow charging
P_{trans}	voltage transformer loss
P_t	thermal loss
P_T	power on output terminals
$P_{(z)}$	service fees charged respectively to charging strategy z
q	quantity
r	bus route
rv	residual multiplier
R_{cable}	resistance of power cable
R	repair cost
RV	residual value (vehicle depreciation)
S	subsidies
S_{BEB}	travelled mileage
t	bus route trip time
t_c	trip time to and from the charging station
t_{trans}	time of electricity transmission per day
T	tax on BEB
u	rate of highway tolls by BEB
UF	utility factor
v	velocity
v_c	constant velocity
v_f	final velocity
v_i	initial velocity
$\tilde{v}_{rj}$	weighted normalized aggregated fuzzy number
$\tilde{V}$	weighted normalized matrix fuzzy decision-making matrix with $\tilde{v}_{rj}$

VP	vehicle price
w	wind speed in driving direction
$\widetilde{w}_j$	aggregated fuzzy weight with $\left(w_1, w_2, \cdots, w_j\right)$
$\widetilde{w}_j^p$	weightage of criteria with $\left(w_1^p, w_2^p, \cdots, w_j^p\right)$
$\tilde{x}_{rj}$	aggregated fuzzy rating with $\left(a_{rj}, b_{rj}, c_{rj}\right)$
$\tilde{x}_{rj}^p$	linguistic terms of the p^{th} decision maker with bus routes r and influential factors j
y	bus type
yr	vehicle age
z	charging strategy
Z_e	travel annoyance multiplier
α_-	deceleration velocity
α_+	acceleration velocity
η	accumulated efficiency factor
η_{AU}	efficiency factor of auxiliary load
η_{BAT}	efficiency factor of BEB battery
η_{INV}	efficiency factor of DC/AC convertor
η_{PMSM}	efficiency factor of permanent magnet synchronous machine
η_i	efficiency of the i-th element
λ	fitting parameter for CVKT
μ	fitting parameter for vehicle age
ϕ	slope gradient
ϕ_S	probability of recharging with a public slow charging
ϕ_f	probability of recharging with a public fast charging
$\phi_{(z)}$	probability of recharging respective to charging strategy z

AHP	analytic hierarchy process
ASEAN	Association of Southeast Asian Nations
BEB	battery electric bus
CB	conventional bus
CO_2	carbon dioxide
EB	electric bus

FCEB	fuel cell electric bus
GDP	gross domestic product
GEI	green energy index
GHG	greenhouse gas
GIA	gini index approach
GMI	green emission index
GNI	green noise index
GPI	green performance index
HEB	hybrid electric bus
LCOE	levelized cost of electricity
MCDM	multi-criteria decision making
PCO	perceived cost of ownership
SDG	sustainable development goal
TCO	total cost of ownership
TOPSIS	technique for order of preference by similarity to ideal solution
UTAR	Universiti Tunku Abdul Rahman
WTW	well-to-wheel analysis

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CHAPTER 1

INTRODUCTION

1.1 General Introduction

In the modern era, greenhouse gases (GHGs) from any form of human activity are the biggest cause of climate change today (Intergovernmental Panel on Climate Change, 2023a). GHG is any gases such as carbon dioxide (CO_2), methane and nitrous oxide that are originally in the atmosphere which absorb and reemit heat and therefore keep the planet's temperature warmer than outer space. However, rapid industrialisation and civilisation break the balance of GHGs in the atmosphere, which leads to global warming and climate change (Brander and Davis, 2012).

Breaking down GHG emissions, the transportation field is the second largest contributor to global emissions (Ritchie, Rosado and Roser, 2020). Taking an example in Malaysia, Abas et al. (2017) revealed that the country contributes 0.3% of global GHG emissions. The percentage shown may not be as high as the other countries. Still, when looking at the Association of Southeast Asian Nations (ASEAN), it is one of the countries that accounts for more than 90% of the ASEAN region's total GHG emissions (Amheka et al., 2022). In contrast to the emissions intensity of gross domestic product (GDP) in 2005, Malaysia by that time aimed to lower its GHG emissions intensity of GDP by 45% by 2030. Meanwhile, it is very interesting to find out that Malaysia's share of coal-fired energy is rising while the other nearby nations are progressively shutting down their coal-fired power plants (Chong et al., 2019).

Here's another question: what makes the transportation system position itself in the top rank? It is fossil fuel that has always been the answer to this question. Since the Industrial Revolution 1.0 started, a new energy source had been unlocked: fossil fuels, energy from coal, oil and gas. Every coin has two sides, it solely helps the rapid development of technology and civilisation at the same time they produce a large amount of CO_2 (Ritchie, Rosado and Roser, 2020). Since then, the transportation and power sectors have become the biggest benefiters from this new energy resource globally and the largest global climate change driver (Ritchie and Rosado, 2017). Thus, the introduction of an electric bus (EB) as a practical form of public transportation appears to be a commendable endeavour to promote environmentally friendly mobility (Doucette and McCulloch, 2011).

Over the past years, alternative fuel vehicles with low-carbon fossil fuels have replaced internal combustion engine vehicles to tackle the global warming issue (Kalghatgi and Johansson, 2017). Other than using a low carbon footprint fossil fuel, vehicle electrification is the key turning point in the trend to substitute the traditional energy generated from burning fossil fuels. In the current market, there are already a lot of operationalized EBs on the road. Generally, the three most common types of EB are battery electric bus (BEB), hybrid electric bus (HEB) and fuel cell electric bus (FCEB) as illustrated in Figure 1.1 (Keller et al., 2019). Three different types of buses consist of unique operating features that are separated from each other. From the perspective of power supply, BEB relies on the electricity that is stored in an onboard battery package to supply power to the wheels while HEB relies on both internal combustion engines (fossil fuels) and electric motors (electric) to generate power. On the other hand, an FCEB relies on electricity generated from hydrogen through an electrochemical process to power the electric motor. In contrast, the energy consumption for BEB is lower than the FCEB but BEB is highly sensitive to the distance of range travelled than the FCEB (Muñoz, et al., 2022).

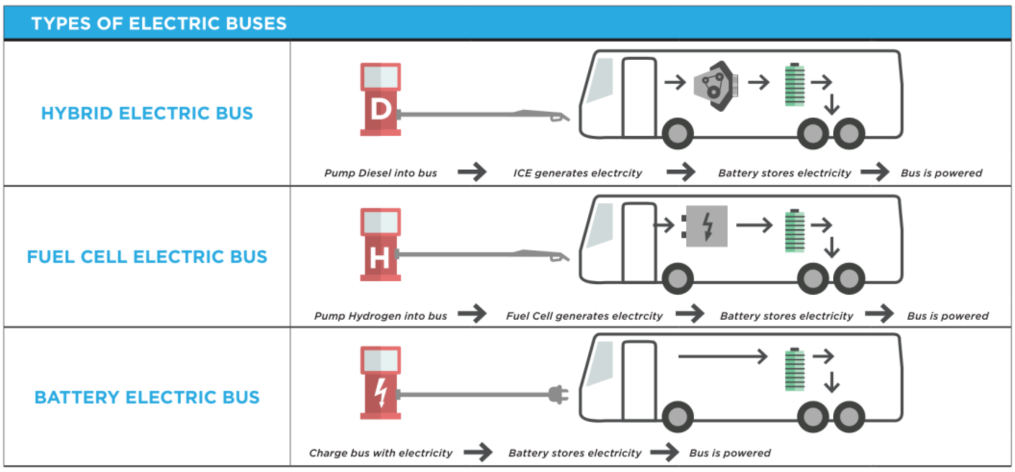

Figure 1.1: Types of Electric Buses (MRCagney, 2017).

Apparently, conventional buses (CBs) consumed a high volume of diesel fuels during the peak hours. However, energy reduction can be achieved by BEB since the electricity is not likely to be affected by traffic conditions. Thus, BEB's energy consumption is much lower than CB during traffic jams (Ma et al., 2021). Not only that, BEB helps to reduce diesel fuels used by an average of 86%. From a lifecycle perspective, BEB saves the fossil fuel used at 46% and reduces up to 35% of GHG emissions (Zhou et al., 2016). Replacing just one CB with an EB could result in annual savings of over 25 tons of CO_2 emissions (Ramasesha, 2016). Interestingly, BEB tended to cut more CO_2 emissions than CB when it was moving at an average speed. (Mao, Li and Zhang, 2021). Therefore, BEB possesses a higher potential to reduce CO_2 emissions (Lajunen and Lipman, 2016). From the overall sustainability and energy management viewpoint, HEB is the best passenger bus in short to medium-term lifetime while FCEB achieved the best performance in a long-term lifetime (Correa et al., 2017). In this context, a sustainable and environmentally friendly substitute for traditional CB, like EB for public transportation, offers a chance to reduce GHG emissions and enhance air quality in big cities across the globe (Pojani and Stead, 2015). Operating an EB proves to be a superior long-term option compared to a CB. In essence, the implementation of EB stands out as one of the most efficient strategies to alleviate environmental challenges (Juan et al., 2016).

Considering economic aspect, the EB can be economically competitive with CB at the average length of lifecycle cost (Lajunen, 2018). The overall cost for a CB is 10% lower than an electric bus only at a 10-year lifetime (Potkány et al., 2018). The early stage of operating an EB requires two to three times that of a CB but the ongoing expenses are so much lower and thus seem to be a considerable option for long-term benefits. (Sheth and Sarkar, 2019). In addition, BEB will soon be economically competitive with CB counterparts as the price of batteries is expected to drop significantly in the next few years (Berckmans et al., 2017). In general, BEB is a better choice to cut energy use and emissions from the sustainable view while it is also economically feasible (Lajunen, 2014).

To design an efficient and viable multi-criteria green fleet network, it is essential to balance the correlation between supply and demand aspects

(Ceder, 2007). While environmental and economic considerations are the concern of bus operators, passenger demand significantly impacts the bus network design process, which is central to planning public transportation operations. In other words, increasing ridership demand requires excellent customer service and effective fleet planning that can reduce traffic congestion and pollution, benefiting the entire community. Compared to CB, EB is eventually more responsive to changes in ridership (Ma et al., 2021). In the meantime, the progress of bus electrification is spreading faster than expected and is going to replace the CB in the next ten years (Pagliaro and Meneguzzo, 2019).

1.2 Importance of the Study

When environmental issues keep growing, human health risks may arise from the greenhouse effect. Starting from the rise in global warming which results in the melting of polar ice followed by the rising of sea level. It later threatens biodiversity, and some species of wildlife soon to extinct. In a more serious case, many coastal cities could become historically forbidden underwater cities in the future (Mikhaylov et al., 2020). Climate change and extreme weather events cause natural disasters such as flood and wildfires which critically affects the development of human communities. The issues stated over and over, a series of protocols such as the Kyoto Protocol has been reached and agreed upon by the world's nations to combat global climate change. Efforts have been put in to implement the regulations in public transportation to cut emissions, and lower the energy used at the end to support renewable resources (Mahmoud et al., 2016). Bearing in mind, transforming from a CB into an EB is not just about purchase and drive. Therefore, an appropriate and comprehensive framework to qualify sustainable public transportation is needed in such a way that it won't aggravate the global temperature issue but is environmentally friendly at the same time.

Strategically, a good planning framework in supporting the bus operation helps to decide the operating route that minimizes the energy usage such as carbon footprint to improve the energy efficiency of the transit system. Moreover, it helps to minimize the CO_2 emissions from public transportation and further ensures a cleaner and healthier urban environment. From the total operating costs point of view, it enables the authorities to make economic decisions that maximize their resource allocation and also improve their financial account. Consequently, the public transit system can mitigate the negative environmental impact while enhancing the financial performance and service quality.

Considering the anticipated growth in population and transportation demand, an assessment of the current transportation infrastructure is indeed required. As the root cause of the global environmental issue is the increasing demand for vehicles, it is also important to determine the bus type, quantity, and frequency to support the deployment and design of the best operating system. It is of great essential to help the authorities maximize fleet efficiency based on green viability to meet diverse operational requirements.

Generally, a multi-criteria green fleet planning framework for a heterogenous EB operation system can support desirable operating routes by considering both environmental and economic considerations. Indirectly, it extends the achievement of the sustainable development goals (SDG) 7 and 9. This framework contributes to SDG 7 by ensuring access to affordable, reliable, sustainable energy through the adoption of EB. Suggesting that electric energy in the transportation sector decarbonize the energy system then further ease the rapid growth of global warming. Furthermore, this framework aligns with SDG 9 by fostering resilient infrastructure development and promoting inclusive and sustainable transportation infrastructure. In line with several decision supporting, this strategy makes clean and green energy services available to citizens.

1.3 Problem Statement

A staggering 8 billion tons of GHGs were released, constituting approximately 24% of the total energy-related emissions around the globe. Notably, three-quarters of these emissions come from road travel, with passenger vehicles comprising cars, buses and trucks (Ritchie, 2020). The majority of GHG emissions are produced by the transportation industry over 28%, more than a quarter. Specifically, the combustion of fossil fuels in vehicles such as cars and buses is identified as the primary source of transportation-related GHG emissions (Intergovernmental Panel on Climate Change, 2023b). Further analysis found that burning fossil fuels for transportation and power is the main GHG emissions human activity-related source. Over 94% of the fuel used is gasoline and diesel, making up the majority of the petroleum-based fuel used in transportation (EPA, 2024).

Recognizing that EB is key in decarbonization, it is also understandable that the biggest obstacle to implementing an EB is the total cost of it, which is not only on purchase cost but also the maintenance, operation and non-monetized cost (Rodrigues and Seixas, 2022). The worldwide supporting rate of electrification is limited as it is found that the retail price is considered high especially the pricey battery (Lindsay, 2016). The price tag of an EB costs twice as much as buying a regular bus. This is the obstacle to reaching 'net zero' by 2050 (Bernama, 2023).

Additionally, bus operators prioritize passenger demand for bus services, as it directly impacts their revenue and is crucial for improving their financial performance. While meeting passenger demand is important, finding a balance between passenger load and pollution control is challenging. Higher demand leads to more passengers, which in turn results in higher energy needs and pollution. Therefore, a well-designed transit network that considers bus frequency, quantity, and capacity is essential for enhancing passenger needs, minimizing environmental impact, and managing overall costs.

1.4 Aim and Objectives

The objectives of this project are listed below:

(i) To propose a viable multi-criteria green fleet planning in supporting electric bus operations.

(ii) To determine a desirable operating route for electric buses with both environmental and economic considerations.

(iii) To determine a heterogeneous electric bus planning to support the operating system.

1.5 Scope of the Study

Among all the EB, this project focuses on BEB only. The reason for choosing BEB is its low maintenance expenditures, low pollutants, and low noise levels (Pelletier et al., 2019). To determine a desirable operating bus route, this project further focuses on the macroeconomic aspect, which is one of the key factors in influencing the adoption of the BEB. Two different aspects are taken into consideration, which are the environmental impact and economic cost. In terms of the environmental aspect, energy consumption and energy emissions are analyzed. The former focuses on evaluating the amount of energy used when driving a BEB, the latter focuses on reducing CO_2 emissions for each bus route. In terms of the aspect of the economic cost, the analysis involves evaluating the expenditure associated with operating a BEB.

With the macroeconomic aspect as a criterion, this project proposes a methodology for determining the desirable bus route to be electrified with a fuzzy TOPSIS (technique for order of preference by similarity to the ideal solution) as the evaluation tool. In addition to the supply (macroeconomic) standpoint, this project also considers another influencing factor which is the passenger load factor representing the demand aspect. It helps to examine how the occupied capacity affects the determination of the best route for electric bus operations. The fuzzy TOPSIS method also incorporates three cost criteria (energy consumption, energy emissions, and cost) and one benefit criterion (load factor) in the decision-making process. All in all, this project analyses how the EB and CB complement each other.

1.6 Contribution of the Study

This study makes significant contributions to the field of sustainable public transportation by addressing critical aspects of electric bus operations and planning. The key contributions of this study are as follows:

- Closing a research gap: This study proposes a detailed five-step framework for green fleet planning, integrating environmental and economic considerations into the decision-making process for electric bus operations. By combining factors such as bus frequency, bus quantity, and passenger load factors, the framework offers a robust approach to support electric bus fleet management.
- Comprehensive evaluation assessment: The research applies the proposed framework for demonstrating the feasibility and effectiveness of the proposed approach in a specific context. Through detailed

analysis, identify the most favourable bus routes and types for EB operations.

- Contribution to decarbonization goals: The study supports the broader goal of reducing the environmental impact of public transportation by providing a structured approach to electric bus fleet planning. The findings contribute to the development of more sustainable and economically viable public transport systems, aligning with SDG targets.

1.7 Outline of the Report

The five chapters of this project are the Introduction, Literature Review, Methodology, An Illustrative Case Study, and Conclusion and Recommendations. The first chapter provides a comprehensive overview of current EB technology, including the context and significance of adopting electric buses in the pursuit of decarbonization. It outlines the main objectives and the scope of the study. This section sets the stage for understanding the challenges and opportunities associated with EB operations. The Literature Review chapter explores existing research and knowledge related to green environment management, fleet planning, and multi-criteria decision-making methods. It identifies gaps in current research and highlights the contributions of previous studies in the field. The Methodology chapter details the research approach and techniques used to achieve the project's objectives. It describes the three supply aspects (energy consumption, energy emissions and PCO) with fuzzy TOPSIS method and the framework for evaluating bus routes and types for electrification. This section also covers data collection processes including the conduct of survey form. The Illustrative Case Study chapter presents a practical application of the methodology using a specific case study. It details the analysis of bus routes and bus types and analysis of the supply and demand aspect. This section demonstrates the application of theoretical concepts to real-world scenarios, offering insights into the most suitable routes and buses for BEB operations. Finally, the Conclusion and Recommendations chapter summarizes the key findings of the project, reflecting on the effectiveness of the proposed green fleet planning strategy. It discusses the implications of the results for electric bus operations and offers recommendations for future research and practical implementation. This section highlights the project's contributions to sustainable public transportation and guides for improving electric bus planning and operations.

CHAPTER 2

LITERATURE REVIEW

This section begins with an overview of EB, looking at the current challenges and trends encountered when implementing EB in the world. Additionally, it discusses the relevant studies that assess the environmental, economic, and demand aspects as well as the performance of EB. It ends with a review of fuzzy TOPSIS by looking at the development of fuzzy TOPSIS and some real-life applications.

2.1 An Overview of Electric Bus

Al-Ogaili, et al. (2021) studied the foundation work on EB innovations that have been initiated. A review of the technical specifications of EB was conducted to determine the feasibility of replacing an EB. First of all, it was found that there is a lack of EB implementations, especially in large-scale operations. The reason is the lack of policies provided to private sector partners to support the electrification of public buses. As a result, no other private parties are willing to take action thus leading to current manufacturing technologies being left behind. Generally, the idea of electric bus implementation is surrounded by many benefits, but fossil fuels are still the unwavering primary energy resource. Therefore, the beneficial solution to reduce GHG emissions is not to replace diesel and natural gas buses with EBs soon. They proposed a general model for full life cycle assessments of EB, including examining benefits, risks, and influences. However, their proposed methodology focuses on GHG emissions instead of CO_2 emissions, which is one of the core considerations in this project.

A literature review was done by Manzolli, Trovão, and Antunes (2022) with three approaches (content analysis, quantitative meta-analysis, and science mapping). From the point of energy management, they found out that machine learning programming and model predicting can efficiently support energy management strategies. From the point of sustainability, EBs are on the verge of reducing their carbon footprint when compared to CBs. They further highlighted the need to use clean energy to lessen the environmental effects.

Since battery degradation directly affects the operation costs, li-ion ageing mitigation techniques become interesting research issues. From the point of battery technology, the effects of a vehicle's cradle-to-grave shall also be conducted carefully to provide consequences on the environmental effects of battery disposal. From the point of fleet operation, the key research direction includes addressing battery and bus route sizing issues, charger installation location and cost reduction while energy consumption is an additional point to enhance the green energy of EB operation. Their literature review showed that EB technology has matured from the majority of studies. Apart from their findings, there are still some open issues to be investigated such as dynamic fleet management strategies, grid impact and interaction and environmental impact analysis.

2.2 Environmental Aspect: Energy Consumption

Teoh et al. (2018) analysed the environmental benefits of replacing the CB with EB. To study the energy demand, they calculated annual energy consumption, annual energy consumption per travelled distance and battery limit fulfilment. By restricting the energy limit of every bus, it was found that the energy used by EB outperformed the CB in every single bus route. Their result concluded that the EB demands the least energy and can replace the CB. However, they restricted the energy demand and the consumption rate remains within 60% of the battery capacity. Since this project aims to propose a charging strategy to enhance bus efficiency, this restriction may not accurately reflect the whole performance of EB in operations.

In evaluating and enhancing environmental sustainability in EB operations, Teoh et al. (2020) developed an assessment framework for determining the energy consumption level of EB operations. They used the green energy index (GEI) to evaluate energy consumption levels. When the GEI index is close to zero, indicating that EB is consuming less energy. On the other hand, the level of energy consumption is considered high when the GEI index is near one. Their result found that passenger load is suggested to increase to lower the energy consumption. The strength of their model is providing an index for the authorities to determine the level of energy consumption. However, a notable weakness is they focused only on the energy demand while the bus was driving on the road and ignored the energy demand while BEB was charging.

To find out the energy consumption on the daily routine of an EB without battery restriction and consider the energy demand in charging stations, Al-Ogaili, et al. (2020) comprehensively established a model in identifying the energy consumption of BEB and further supported the bus electrification networks. Their proposed methodology focused on the energy used by BEB by calculating the required energy when the bus runs on the road and energy loss when charging in the charging station. Their outcome demonstrated that the high route gradients and passenger load contribute to the high energy consumption of BEBs. Besides, it is suggested that a small battery be used for bus routes with low energy demand per trip. Conversely, a large battery size can be implemented on buses that require high energy consumption per trip. Subsequently, their findings indicated that buses with smaller battery sizes benefit from opportunity charging while those with larger batteries benefit from overnight charging. However, the initial stage for installing BEBs requires careful consideration of the other aspects besides energy consumption. It is found that the electricity charges could affect the bus distribution network and later impact the whole EB management system. To fill up the limitation of their paper, this project cooperates two more factors such as energy emissions and cost analysis to decide the desirable route for electric bus operations.

2.3 Environmental Aspect: Energy Emissions

Generally, well-to-wheel analysis (WTW) is a well-used tool to evaluate the GHG emissions of buses during the fuel production and provision stage and bus operation (Xylia, M. et al., 2018). Teoh, Goh and Khoo (2020) integrated the WTW analysis model and proposed the green emissions index (GMI) to determine the level of GHG emissions. Their findings showed that increasing load factor and reduced bus frequency helped lower emissions. The strength of their assessment is that they set the standard to determine the level of energy emissions performance, especially focusing on GHG emissions. However, this project focuses on CO_2 emissions, the major component that contributes to the major proportion of GHG emissions. In light of this, their paper might have offered some useful insights but it isn’t particularly helpful for this project.

To examine the CO_2 emissions, Zhang, et al. (2021) conducted a comparative analysis between CB and BEB. By comparing both types of buses, the CO_2 emissions of BEB are down around 25% compared to the CB. In short, BEB can substantially decrease the CO_2 emissions. They provided an easy but strong methodology to obtain the CO_2 emissions only, based on the calculation comparison between CB and BEB. It is far from enough to determine the desirable bus routes to replace CB with BEB. To fill up the gap, this project incorporates their methodology in calculating the CO_2 emissions and then offers an evaluation tool to assist the bus authorities in deciding the most suitable bus route for electrification instead of blind picking.

2.4 Economic Aspect: Cost

This section dives into the viewpoint from the economic aspects when evaluating the feasibility and sustainability of transitioning to BEB. It covers the levelized cost of electricity, financial analysis, total cost of ownership, and perceived cost of ownership, offering a comprehensive exploration of the economic landscape surrounding BEB implementation.

2.4.1 Levelized Cost of Electricity

Levelized cost of electricity (LCOE) is a methodology for comparing the cost of different electricity charging types. It calculates the installation expenses and ongoing costs like insurance, and maintenance (Cambell, 2008). The highlight of this method is to find the ratio between total lifetime operation cost and energy production, where its main focus is on the net value spent by every unit of electricity used. From the comparative analysis, BEB can reduce about 81% of the driving cost, where which can alleviate the financial burden on transit operations to a certain extent. Moreover, the slight increase in the discount rate for bus users led to an increase in LCOE but did not pressure the enterprise much. Overall, the hybrid charging mode is more favoured than the fixed charging mode as it impacts the LCOE (Zhang et al, 2021). A commendable method was suggested in comparing the cost of electricity but are only limited in comparing electricity fees between two different charging modes of BEB. In other words, their methodology does not overview the cost for the whole operation lifetime cycle of a BEB.

2.4.2 Financial Analysis

Teoh et al. (2018) examined the potential financial analysis between CB and EB by considering the annual cost, revenue, profit and cost per energy consumption. Their result showed that EB lowers the annual cost by up to 48% while saving 35% of the average annual cost ratio per energy demand. Consequently, this resulted in a huge improvement in annual profit, 94%. A better idea of analysing the whole lifetime financial view could be seen from the comparison between CB and EB. Their strength is providing a financial view for authorities to see the profit of swapping from CB to EB. However, the weakness is the lack of cost analysis, in which only the annual cost is included in this paper. Alternatively, they did not consider the entire lifespan costs associated with BEB.

2.4.3 Total Cost of Ownership

Wabe and Coles (1975) proposed an economic model for cost analysis, dividing the total cost of consumption into fixed and variable components. Then, Majumder et al. (2021) modified the economic model to develop a new total cost of ownership (TCO) model. It involves numerous cost components (installation, maintenance, and operation costs). The installation expenses include the purchase of EB and its charger whereas the maintenance cost covers the preventative and propulsion service fee for both EB and charger. The operation expenses calculate the labour and electricity costs. They revealed that the CB system exhibits the highest variable cost, indicating the TCO of BEB is lower than CB. Their findings show that even though the initial and fixed cost of operating EB is three to four times greater than that of a CB, the variable cost is still much less. As a result, the system's deployment is more affordable and has a larger contribution from renewable energy sources. However, their methodology model overlooked the non-monetizable cost component such as the inconvenience caused if the selected BEB fails to match the travel demand consequently leading to delays while waiting for a replacement BEB to arrive.

2.4.4 Perceived Cost of Ownership

Since the TCO model didn't present the intangible and non-monetized expenses. Hao et al. (2022) innovated the model and further covered the expenses without the exchange of cash such as the repower annoyance cost, range anxiety cost and alternative vehicle cost that will indirectly pressure the TCO. There are a total of six components in the perceived cost of ownership (PCO) model: vehicle cost, insurance cost, energy cost, implicit cost, maintenance and repair cost, and taxes and fees. They found out that the CB is the most economical public transit in China's current market while FCEB and BEB are still considered not affordable by most of the bus authorities. High implicit cost is the main factor that causes the problem in the electrification of buses, so that is suitable to raise the electric range by expanding the battery size. However, with the increase of EB's electric range, the PCO would also rise. This is because the reduction in implicit costs is outweighed by the increased purchase cost associated with a larger battery. Other than that, the optimal driving range for BEB is 300km but is categorized as not economically feasible in a longer driving range. In addition, BEB is more likely to be the first to dominate mini and midsize buses in the 5-year cash flow length. Thus, to lower the implicit cost for BEB, a battery-swapping strategy is suggested to make them a more competitive option for buses. They introduced a comprehensive reveal of the real economic costs and cash flows of operating EBs. However, solely relying on cost consideration is insufficient to determine the optimal bus route for electrification. Hence, an additional analysis of energy consumption and emissions alongside PCO is to be thoroughly discussed in this project.

2.5 Demand Aspect: Passenger Load Factor

Yu et al. (2016) determined the impact of passenger load on fuel consumption and emissions from CB. To evaluate the effect, the recorded passenger load values were divided into four segments: 500–1000kg, 1000–1500kg, 1500–2000kg, and over 2000kg. As the speed rose from stationary to over 40km/h, the impact of the passenger load on emission rates became more noticeable. The CO_2 emission rate with the largest passenger load at high speed could be three times higher than that of a low passenger load (500–1000kg). Furthermore, higher passenger loads during acceleration generally result in higher pollutants and fuel consumption. On the contrary, the number of passengers did not affect the emissions and fuel consumption rates during deceleration. While driving at the average speed, all passenger load groups showed a declining trend in fuel consumption and emission parameters. They assess the driving velocity and examine its effects on the CB emissions and fuel consumption rates. However, this project focuses on BEB instead and studies the impact of passenger load factor on electric bus operations.

Liu et al. (2019) compared CB and BEB on the effect of changes in mass varying from the realistic passenger loading over a day on energy consumption. The future automotive systems technology simulator calculated the amount of fuel CB needs to refill and the recharging time that BEB requires from fast charging under three different passenger load combinations (zero, maximum and time-varying). Regardless of the type of buses, their result showed a positive association between passenger load and energy consumption. Energy consumption rises as more people are on board in which a fully loaded CB uses 34% more energy while a BEB uses 23% more energy than an empty bus. Besides, they found that the energy needed to overcome drag coefficients is constant under any speed but the growth of the passenger load raises the energy to accelerate the vehicle and rolling resistance. However, BEB's capacity to recapture the energy permits it to be less affected by payload on its energy usage. That is because the overall kinetic energy of the BEB rises with its mass, giving it more energy to recover during braking situations. Comparatively, both kinds of buses have higher energy usage as their weight increase but compared to CB, BEB is less sensitive to mass variations. Understanding passenger load is crucial for a transit agency when choosing the most desirable bus route or battery size. However, relying only on estimating energy usage based on passenger load may not provide sufficient information. Energy emissions are also essential to be considered to ensure a comprehensive environmental assessment.

Zacharof et al. (2023) investigated the impact of various environmental factors, such as passenger load, temperature, and solar radiation on auxiliary energy consumption and CO_2 emissions from BEB. Their study assessed the mass variable of BEB at different passenger occupancies (0%, 25%, 50%, 75%, and 100%). When the temperature is between 10°C - 20°C, they found that higher passenger occupancy reduces auxiliary energy demand due to human-emitted heat but increases CO_2 emissions. In extreme scenarios where low temperatures low solar radiation and no passengers, energy consumption can increase by up to 185%. Additionally, vehicle mass significantly influences power demand during acceleration and uphill driving. In the case of long slopes, variations in passenger numbers have a serious impact on CO_2 emissions. Nevertheless, not much research has been done on how changes in passenger load affect the operational performance of BEB in the economic aspect.

Amiripour et al. (2014) designed an efficient and flexible bus network capable of effectively managing demand across all seasons to address the issue of seasonal fluctuations. Zhang et al. (2024) introduced an optimization technique enabling electric buses to dynamically adapt to real-time passenger demands within a pre-travel booking framework, where passengers plan their trips ahead of time. Their approach optimized routes and schedules effectively by anticipating passenger volumes, significantly reducing transit times and operating costs. As the passengers board and alight at bus stops, the total bus mass fluctuates accordingly. This variation significantly impacts energy consumption, especially when driving in hilly or uphill terrain. The relationship between passenger load with energy use and costs is generally well discussed. However, there is a gap in guidance on identifying the most suitable bus routes for electrification. Thus, this project proposes a planning framework to assist bus operators in making decisions to address this gap.

2.6 Electric Bus Performance

Zhang et al. (2021) conducted a comparative analysis between fixed and hybrid charging modes to determine the best charging mode with the best efficiency between CB and BEB. Speaking of fleet planning strategy, the hybrid charging mode is the answer to the issue of insufficient parking spaces available for charging during busy hours. Moreover, given that BEB might encounter emergencies like power shortages, hybrid charging piles in nearby charging stations allow for instant power supplementation. Their findings provided valuable insight into charging strategies but ignored two important components in determining heterogenous EB planning: bus frequency and bus quantity.

Teoh et al. (2018) outlined EB network design from other aspects than charging strategies such as the characteristics of a bus route. Their proposed methodology consists of four main stages: model development, data collection and compilation, traffic and transit system calibration and validation, electric bus network design and fleet planning. With the number of EB and charging facilities, the increased bus route leads to an increased number of buses. The low number of buses is due to the employment of fast charging stations further implies that short charging duration offers a low number of bus operations. Moreover, the reason for high bus frequency is because of the high number of bus routes. Based on the bus performance, it was concluded that the distance travelled and total number of passengers of EB is better than CB. That’s because the fast-charging facility helps to load more passengers. Lastly, the increased bus route found that it increased 49% of passengers, and the total number of passengers using EB increased by 2%, specifically 49% of passengers per bus. It is crucial to recognize that the shift from CB to BEB is solely driven by several factors. These include socioeconomic aspects, passenger preferences and bus service attitudes such as waiting time, reliability and punctuality. Thus, looking into the potential mode transition in more detail is necessary.

Teoh et al. (2020) intended to improve the overall green performance of the EB operating system. The gini index approach (GIA) was used to identify the green index of each environmental factor (GEI, GMI and green noise index (GNI)). Later, they applied the weighted-grading approach to integrate the obtained green indexes with a specific weight for each factor. Lastly, the green performance index (GPI) was quantified to evaluate the overall green performance. In summary, the increased passenger load helps the most in increasing the average GPI, followed by the reduction of bus frequency and the reduction of bus seats. However, the weightage shall be selected with care as it may influence the result much.

Later, Teoh et al. (2021) improvised a better model to determine EB's more accurate green performance. The proposed methodology involved multiple decisional criteria based on government policy, financial cost, bus specification and passenger feedback that constitute the overall green weightage of EB. The analytic hierarchy process (AHP) approach was used to integrate the decisional criteria for determining the respective weightage for the green index. From their findings, the lower bus frequency and increased passenger load effectively improve the GPI while the smaller bus capacity improves the GNI. EB operators may attract more passengers by offering discounted or seasonal bus fares to increase the load factor. A punctual and comfortable bus should be provided to retain the existing passengers. Heterogeneous EB with varying bus sizes can be incorporated to yield a greener performance. Although they presented a proper methodology for computing the environmental performance of the EB network, they did not discuss the characteristics of charging facilities in which the different types of charging methods that are crucial in influencing energy consumption.

Goh (2022) extended the methodology from Teoh et al. (2021) by incorporating two additional operating characteristics: reduced bus speed and different charging strategies. Two approaches were used to determine the green weightage: the first technique employed three self-defined weighting sets, and the second approach used AHP. Reducing bus speed showed the largest gain in GNI, followed by GEI and GMI, but the GPI displayed the same score and grade as the benchmark, indicating no improvement. Switching from slow to fast charging technology significantly improved GMI and gradually improved GPI, with each increase in battery charging efficiency resulting in a 2.36% improvement in GPI. The order of improvement level for GPI is as follows: increase passenger load, adjust bus frequency, adjust bus capacity, switch charging strategy, and reduce bus speed. The results showed that passenger load was the most crucial factor in achieving greener bus operations. Therefore, this project aims to use this valuable reference to quantify the socioeconomic performance of EB operational systems, considering both environmental factors and cost aspects that were not explicitly covered in her work.

2.7 Fuzzy TOPSIS

TOPSIS was first introduced by Hwang and Yoon (2012) back in the last century. Since then, it has become the most used mathematical approach among all the solutions to solve multi-criteria decision making (MCDM) problems. However, MCDMs in many real-world scenarios are subjected to unknown constraints, restrictions, and outcomes. Correspondingly, Bellman and Zadeh (1970) presented fuzzy numbers within MCDM for the first time. In most cases, languages and words cannot convey precise meanings or are usually subjected to personal judgement, leading to improper and biased conclusions. Fuzzy numbers are used to express linguistic factors in quantitatively defining subjective judgment. The idea of linguistic terms makes computation possible to compute using words rather than numbers (Zadeh, 1975). The combination of fuzzy numbers and TOPSIS is known today as fuzzy TOPSIS. This section dives into the evolution and development of MCDM and some real-life scenarios using fuzzy TOPSIS.

2.7.1 Overview of Fuzzy Environment

Salih et al. (2019) offered useful insights into how decisions are made in fuzzy environments and provided a logical classification system for the literature review. The MCDM problems arise and are heavily utilised in several fields, including the social sciences, operation research and economics. The basic aim of MCDM is to identify the best candidate from a collection of criteria. Among all types of fuzzy environments used nowadays, the triangular fuzzy type of membership function is the most adopted tool. Furthermore, they found that the number of decision-makers and criteria make choosing the best alternative difficult for certain specific problems, such as selection problems. In evaluation problems, choosing a set of suitable weights for criteria is usually challenging. Using subjective word evaluations to determine random weights for criterion does not ensure effectiveness and reduces decision accuracy. In energy problems, uncertainties such as sector aggregation and linearity assumptions make it hard to incorporate with a fuzzy TOPSIS model alone. Apparently, fuzzy TOPSIS is quite famous among the evaluation and selection problems. Overall, they provided a useful literature review of

MCDM, seeing the trends categorising the benefits and challenges faced, and giving some recommendations.

2.7.2 Overview of Fuzzy TOPSIS

Nădăban, Dzitac and Dzitac (2016) provided an overview of fuzzy TOPSIS development, starting from the theoretical part to the fuzzy MCDM problem formulation and then the real-life application review. Notably, the formulation in the calculation part consists of two parts, fuzzy AHP and fuzzy TOPSIS. The former approach is the current most used method in obtaining the criteria weights where it normalises the linguistic terms assigned by different decision makers. The latter approach aims to find the highest closeness coefficient which is the shortest distance from FPIS and longest from FNIS to rank out the best alternative. All in all, they provided clear concepts of fuzzy TOPSIS along with the calculation formulas.

2.7.3 Location Selection Problem

In the location selection problem, Sirbiladze et al. (2017) used the fuzzy TOPSIS approach to decide the best spot to install an emergency service facility. Using numerical simulation, they aimed to rank the five candidate fire station locations (alternatives) based on six critical infrastructure objects (criteria) in a certain urban area. Most of the time, the objectives are looking for a way to install the least number of facilities to meet every demand point within the service distance. However, the least amount of travel time from candidate centres is more important than the distance covering demand locations in this case. Hence, the radius of the service centre in an extreme environment for emergency planning is established based on the maximum time permitted for travel rather than distance. Overall, it was found that an increase in the number of fire stations indicates a higher level of the fire stations selection ranking index. While they used the shortest travelled time as a reference for selecting emergency service facility locations, this project adopts a different approach is that focus on the distance travelled by bus to calculate the energy consumption, emissions and costs then based on these to determine the optimal route for electrification.

2.7.4 Supplier Selection Problem

For the supplier selection problem, Kumar, Kumar and Barman (2018) used fuzzy TOPSIS to determine the best multi-raw iron and steel suppliers. The best supplier was selected from among four equally certified suppliers to keep competitive in the market based on cost, delivery capabilities, product quality, performance and reputation. Since the outcome fluctuates when the input data changes, the sensitivity analysis is further performed based on fuzzy TOPSIS. Instead of using fuzzy AHP, a total of ten examples have been considered, varying the criteria weights from extremely low to high. The results with and without sensitive analysis bring slightly different conclusions. The supplier with the minimum score remains the same but the one with the highest score differs. Hence, the value of criteria weights is crucial in deciding since they influence the overall performance values. All in all, they contributed to the field of supply chain management, while this project applies the same tool (fuzzy TOPSIS) for evaluation but focuses on contributing to the field of environmental sustainability.

2.7.5 Sustainable and Renewable Energy Problem

In terms of sustainable and renewable energy problems, Awasthi, Chauhan, and Omrani (2011) used fuzzy TOPSIS to select the sustainable transportation system that deals with partial information. Their methodology consists of three main stages. The first stage is to determine the influencing factors. Secondly, they performed the fuzzy TOPSIS along with the linguistic rating collected from experts. Lastly, sensitivity analysis was used to identify the sensitivity of decision-making to the changes in criteria weights. They proposed a clear methodology for using fuzzy TOPSIS to suggest the most sustainable candidate for the implementation of a green transportation system in the city.

Other than that, Emami, Song and Khani (2022) contributed the clarity and framework in identifying the best candidate bus routes for diesel conversion to electric power and discovered the possibility of installing charging infrastructures in bus terminals with TOPSIS method. 14 criteria such as pollutant emissions, passenger load and service frequency were evaluated. They used a nine-point evaluation scale to determine the importance of criteria with AHP. They help the bus authorities in selecting the best routes for electrification, thereby reducing overall operating costs. Apart from evaluating criteria such as land price and air quality, this project was built on a similar concept with a different stance. Eventually, it focuses on three main macroeconomic factors, including energy consumption and cost, which are the key aspects of this project but were ignored by Emami, Song, and Khani (2022).

2.8 Summary

In summary, this section reviewed prior research and works, highlighting the importance of encouraging bus electrification to optimize operating expenses and achieve a lower carbon footprint. While numerous papers discussed sustainable bus networks, there is still a lack of explicit literature on a multi-criteria green fleet planning strategy that supports the operations of BEB. Currently, there appear to be no studies integrating both supply and demand aspects, that cover environmental (energy consumption, emissions) and economic (cost) considerations Apart from that, there is also no existing evaluation using the fuzzy TOPSIS to determine the most desirable electric bus routes. Thus, this project is significant and useful in providing clear and systematic guidance to support electric bus operators in transitioning from CB to BEB.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This project aims to propose a viable multi-criteria approach to green fleet planning that supports electric bus operations. By considering both environmental and economic factors, the proposed framework seeks to identify the most desirable operating routes for BEB. Ultimately, it develops a heterogeneous electric bus plan that effectively supports the overall operating system. As illustrated in Figure 3.1. the methodology of this project involves five main stages, namely: stage 1: determination of influencing factors and EB type, stage 2: data collection, stage 3: design of survey form, stage 4: conduct of survey study, and stage 5: application of fuzzy TOPSIS as the evaluation technique in which the descriptions of each stage are elaborated below.

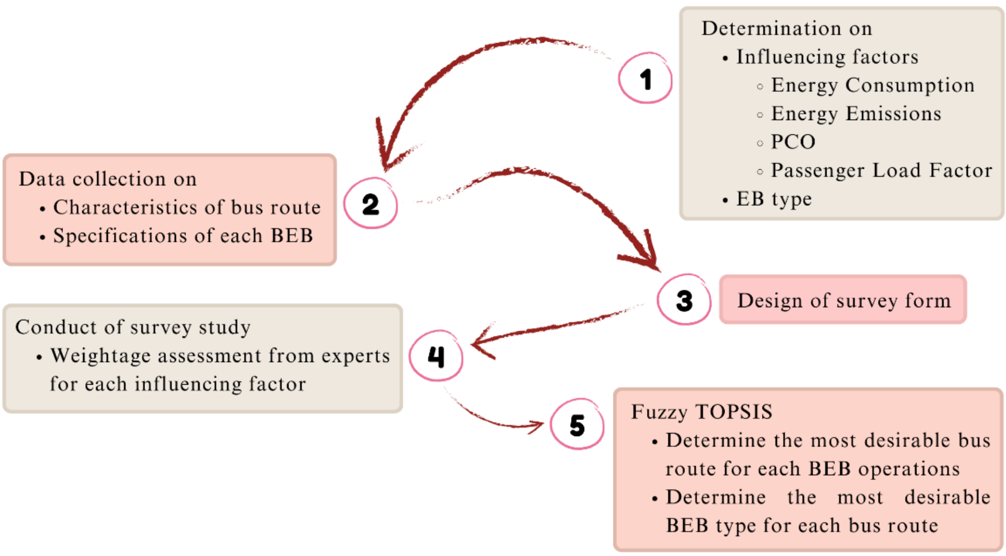

Figure 3.1: Process Flowchart of The Methodology.

3.2 Stage 1: Formulas for Determining Influencing Factors

This section presents the formulation for assessing environmental and cost aspects, beginning with energy consumption, followed by energy emissions, and PCO.

3.2.1 Environmental Aspect: Energy Consumption

According to Al-Ogaili, et al. (2020), the energy consumption of a bus during operation duty can be computed by considering three components, namely mechanical energy, auxiliary energy, and energy loss in the charging station in which each component is described accordingly below.

3.2.1.1 Mechanical Energy

To determine the mechanical energy (E_{mec}) at the wheels, while the bus travelling, the equation can be expressed below:

$$\begin{aligned} E_{mec} = \frac{\eta}{3600}\Big[&(m_{BEB} + n \times lf \times m_p)gC_r cos\phi_n \\ &+(m_{BEB} + n \times lf \times m_p)gsin\phi_n + \frac{1}{2}kaC_d(v-w)^2 \\ &+\left(m_{BEB} + n \times lf \times m_p + m_f\right)\frac{dv}{dt}\Big]d \end{aligned} \tag{1}$$

where η is the accumulated efficiency factor for a BEB, g is the gravity, C_r is the coefficient of rolling resistance, ϕ_n is the slope gradient, k is the density of air, a is the frontal area of a BEB, C_d is the drag coefficient of the BEB frontal cross-sectional area, v is the velocity, w is the wind speed in the driving direction, m_f is the fictive mass of rolling inertia and, d is the route length covered. Besides, the passenger load plays an important determinant and therefore the total mass of the BEB is modified accordingly and it consists of two components, namely the mass of empty BEB, m_{BEB} and the mass based on passenger capacity, $n \times lf \times m_p$ where n is the number of passenger seats, lf is the passenger load factor and m_p is the passenger weight.

The accumulated efficiency factor for a BEB, η can be further expressed as follows:

$$\eta = \eta_{PMSM} + \eta_{INV} + \eta_{BAT} + \eta_{AU} \tag{2}$$

where η_{PMSM} is the efficiency factor of a permanent magnet synchronous machine, which considers the rotor and stator, η_{INV} is the efficiency factor of a DC/AC converter, η_{BAT} is the efficiency factor of BEB battery and η_{AU} is the efficiency factor of auxiliary load, which considers the air conditioner, pumps and radiator fan.

Theoretically, E_{mec} is the general idea in computing the mechanical energy required in wheels while the bus is in operation. However, the fact is that a bus is never going to travel at a constant speed forever but changes according to the road condition. Sometimes, the bus needs to speed up when the slope gradient is too big to climb that hill. On the other hand, while the bus is travelling under bad weather, it is forced to slow down for road safety cautious. To be specific, E_{mec} can be computed based on three scenarios: when bus accelerates, driving at constant speed and decelerates.

The mechanical energy at the wheels when a bus in acceleration (E_{a+}) can be computed as below:

$$\begin{aligned} E_{a+} = \frac{\eta}{3600} & [(m_{BEB} + n \times lf \times m_p) g C_r cos\phi \\ & + (m_{BEB} + n \times lf \times m_p) g sin\phi + kadC_d \alpha_+ \\ & + (m_{BEB} + n \times lf \times m_p + m_f) \alpha_+] d_{00} \end{aligned} \tag{3}$$

where α_+ represents acceleration velocity and d_{00} represents the route length covered in acceleration which can be obtained as follows:

$$d_{00} = \frac{v_f^2 - v_i^3}{2\alpha_+} \tag{4}$$

where v_f and v_i indicate the final and initial velocity respectively.

The mechanical energy at the wheels when the bus is at a constant speed (E_0) can be computed as below:

$$\begin{aligned} E_0 = \frac{\eta}{3600} & [(m_{BEB} + n \times lf \times m_p) g C_r cos\phi \\ & + (m_{BEB} + n \times lf \times m_p) g sin\phi + \frac{1}{2} kaC_d v_c^2] d_{01} \end{aligned} \tag{5}$$

where v_c represents constant velocity and d_{01} represents the route length covered at a constant velocity.

The mechanical energy at the wheels when the bus is in deceleration (E_{a-}) can be computed as below:

$$\begin{aligned} E_{a-} = \frac{\eta}{3600} & [(m_{BEB} + n \times lf \times m_p) g C_r cos\phi \\ & + (m_{BEB} + n \times lf \times m_p) g sin\phi - kadC_d \alpha_- \\ & + (m_{BEB} + n \times lf \times m_p + m_f) \alpha_-] d_{02} \end{aligned} \tag{6}$$

where α_- represents deceleration velocity and d_{02} represents the route length covered in deceleration which can be obtained as follows:

$$d_{02} = \frac{v_f^2 - v_i^3}{2\alpha_-} \tag{7}$$

As displayed in Figure 3.2, E_{mec} can be calculated with every 30 meters travelled and thus the total E_{mec} of a bus route can be determined as below:

$$E_{mec} = E_1 + E_2 + E_3 + \cdots + E_n \tag{8}$$

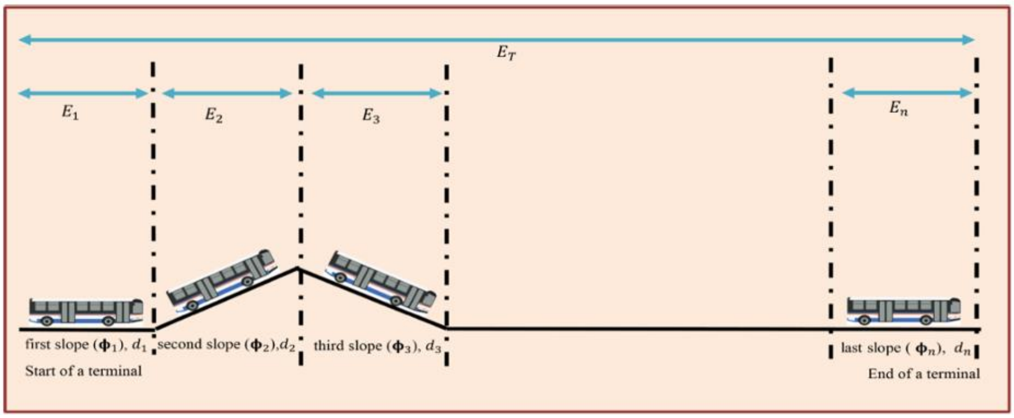

Figure 3.2: The Total Mechanical Energy of a Bus Route for Each 30 Meters Travelled (Al-Ogaili et al., 2020).

3.2.1.2 Auxiliary Energy

The auxiliary energy (E_{aux}) required to run various auxiliary parts such as operating doors, air conditioning, lamps and powered steering can be obtained as follows:

$$E_{aux} = P_{aux} \times t \tag{9}$$

where P_{aux} represents the auxiliary power and t represents the bus route trip time.

3.2.1.3 Energy Loss in Charging System

This section presented a model of Al-Ogaili et al. (2020) estimating energy losses during BEB charging operations as illustrated in Figure 3.3. Generally, the energy loss in the charging station (E_{loss}) is determined by the power loss in the power supply system (P_{loss}) with the time of electricity transmission per day (t_{trans}). It can be computed as follows:

$$E_{loss} = P_{loss} \times t_{trans} \tag{10}$$

where P_{loss} is presented below and it can be determined by the power on the output terminals of the power supply system (P_T) and the efficiency of the i-th element of the transmission system (η_i).

$$P_{loss} = P_T(1 - \prod_{i=1}^{m} \eta_i) \tag{11}$$

For P_T, three major components: transmission cable loss (P_{cable}), voltage transformer loss (P_{trans}) and power electronic device loss (P_{ped}) are substituted respectively to determine the power loss of each component in the power supply system.

Firstly, P_{cable} is described as below:

$$P_{cable} = \frac{3I^2 R_{cable}}{1000} \tag{12}$$

where I represents the required electricity current and R_{cable} represents the resistance of the power cable.

P_{trans} occurs in the transformer while the BEB batteries are being charged. To evaluate its value, five major losses, hysteresis loss (P_h), eddy current loss (P_e), copper loss (P_c), dielectric loss (P_d) and thermal loss (P_t) are considered as below:

$$P_{trans} = P_h + P_e + P_c + P_d + P_t \tag{13}$$

P_{ped} occurs in three-phase rectifiers and AC/DC converters when they are used to convert line voltage to battery voltage. It consists of two forms of loss: stand-by loss (P_s) and Joule effect loss (P_J) as stated below.

$$P_{ped} = P_s + P_J \tag{14}$$

Concisely, the daily energy consumption ($E_{cons}^{y,r}$) of bus type y during the operation duty with the bus route r is computed by:

$$E_{cons}^{y,r} = [(E_{mec} + E_{aux}) \times f + E_{loss}] \times q \tag{15}$$

where f and q represents the bus frequency and bus quantity, respectively.

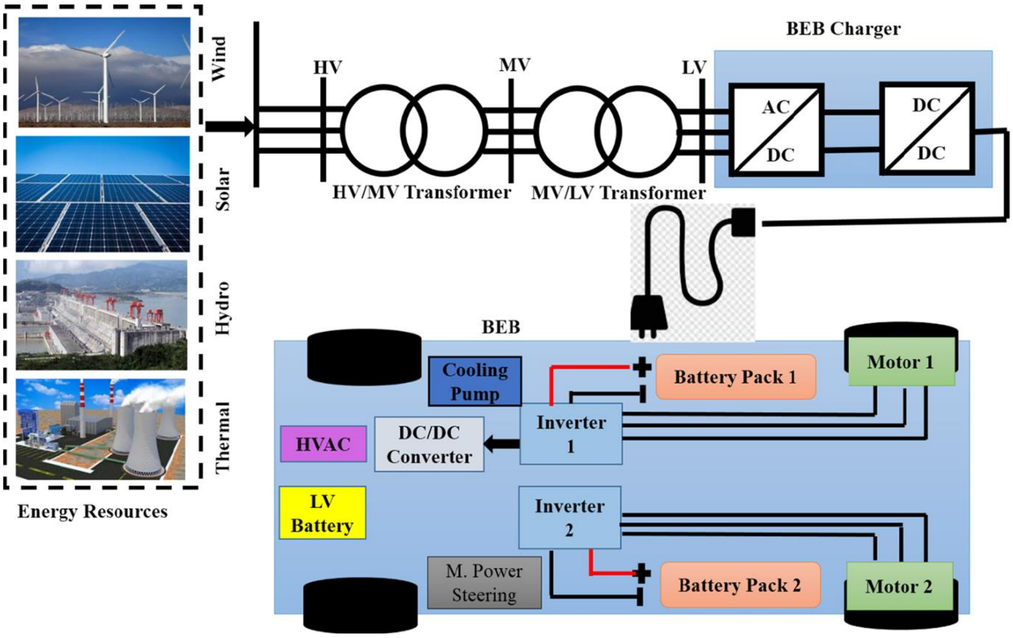

Figure 3.3: The Block Diagram of Evaluating Energy Losses During BEB Charging Operations (Al-Ogaili et al., 2020).

3.2.2 Environmental Aspect: CO_2 Emissions

According to Zhang, et al. (2021), the major power supplied to BEB is electricity. As 1 kWh of electricity produces 0.997 kg of CO_2 emissions (Ming et al., 2017), the CO_2 emissions of BEB (E_{CO_2}) can be calculated as below:

$$E_{CO_2} = 0.997 \times S_{BEB} \times E_{cons}^{y,r} \tag{16}$$

where S_{BEB} is the travelled mileage. Originally, the $E_{cons}^{y,r}$ is calculated in the unit of kWh/km. However, since it already includes the meters travelled per bus trip therefore the modified version of daily CO_2 emissions is shown below, with the travelled mileage neglected.

$$E_{CO_2}^{y,r} = 0.997 \times E_{cons}^{y,r} \tag{17}$$

3.2.3 Economic Aspect: PCO of Electric Bus Operations

The PCO offers a way to compare the cost of different types of new energy vehicles under different scenarios. Considering the monetization of invisible expenditures along with intangible non-monetised expenses, it helps consumers in making decisions about what to purchase. The general model of PCO proposed by Hao et al. (2022) consists of vehicle cost (C_V), insurance cost (C_I), energy cost (C_E), implicit cost (C_N), maintenance and repair costs (C_M) as well as taxes and fees (C_T) as stated below:

$$PCO = C_V + C_I + C_E + C_N + C_M + C_T \tag{18}$$

Since the PCO model is integrated on an annual basis, the methodology proposed by Hao et al. (2022) has been adjusted to derive the daily-basis PCO ($DPCO^{y,r}$) as detailed below.

3.2.3.1 Vehicle Cost

The vehicle cost (C_V) is the initial cost of owning a vehicle and accounting for its depreciation in the current year. It can be computed as below:

$$C_V = P - RV_{yr} \tag{19}$$

The purchase cost (P) is determined by the vehicle price (VP) and subsidies (S), as follows:

$$P = VP - S \tag{20}$$

The residual value (RV) at the current vehicle age (yr) is obtained from the vehicle price (VP) times residual multiplier (rv) at the current vehicle age (yr) as shown below.

$$RV_{yr} = VP \times rv_{yr} \tag{21}$$

where rv can be further determined using the exponential function as described below:

$$rv = e^{(\lambda \times CVKT + \mu \times yr)} \tag{22}$$

where λ and μ correspond to cumulative vehicle-kilometres-travelled ($CVKT$) and yr respectively and are derived from Burnham et al. (2021).

Ultimately, the daily vehicle cost (DC_V) at different yr can be computed as below:

$$DC_V = \left(VP - S - RV_{yr}\right) \times \frac{1}{OP} \tag{23}$$

where OP is the number of days BEB are operated per year.

3.2.3.2 Insurance Cost

As presented below, the annual insurance cost (C_I) includes the liability insurance (I_L), which is mandatory for every vehicle on-road, passenger accident insurance (I_A), another compulsory insurance that depends on the number of seats, supplementary liability insurance (I_S), which covers third-party injuries, is not mandatory and car damage insurance (I_D).

$$C_I = I_L + I_A + I_S + I_D \tag{24}$$

where I_D based on the vehicle residual value can be determined as below:

$$I_D = 280 + RV_{yr} \times 1.088\% \tag{25}$$

By integrating all the components, the daily insurance cost (DC_I) can be evaluated as follows:

$$DC_I = \left(I_L + I_A + I_S + 280 + RV_{yr} \times 1.088\%\right) \times \frac{1}{OP} \tag{26}$$

3.2.3.3 Energy Cost

As presentend below, the accumulated energy cost (C_E) determines the annual cost of electricity of a BEB (F_E), considering discount rate (r) in purchasing a BEB then sums up the cost from the first year ($yr = 1$) to the total ownership time (L).

$$C_E = \sum_{yr=1}^{L} \frac{F_E}{(1+r)^{yr}} \tag{27}$$

where F_E can be estimated as below:

$$F_E = \left[\phi_f(P_E + P_{S-F}) + \phi_S(P_E + P_{S-S})\right] \times AVKT \times EC \tag{28}$$

where the P_E is electricity price, the service fees charged for fast-charging stands for P_{S-F} while slow-charging for P_{S-S}. The probability of recharging with a public fast charger is determined by ϕ_f while a slow charger is determined by ϕ_S. EC is the electricity consumption rate which may be influenced by the total mass of the BEB. Therefore, it may be further indicated as below:

$$EC = EC_{kg}(m_{BEB} + n \times lf \times m_p) \tag{29}$$

where EC_{kg} is the electricity consumption rate per kg and it is assumed to be 0.0024kW/km (Hao et al., 2022). Typically, $AVKT$ refers to the annual vehicle-kilometres travelled covered by a BEB along a bus route. It can be expressed as below:

$$AVKT = UF \times AVKD \tag{30}$$

where $AVKD$ is the annual vehicle-kilometres demand or the annual bus route distance coverage. It can be defined as:

$$AVKD = d_c \times f \times OP \tag{31}$$

where d_c represents the whole bus route length.

Utility factor (UF) represents the distance cost ratio covered based on the BEB battery power. It is obtained by $DVKT$, the daily vehicle-kilometres travelled and all-electric range (AER), the farthest distance a BEB can cover using only power from its battery pack as shown below:

$$UF = PF(\alpha + 1, \beta) + \frac{AER}{mean(DVKT)}\left(1 - PF(\alpha, \beta)\right) \tag{32}$$

where PF is the cumulative probability distribution function of shape α and scale β which can be formed as follows:

$$f(AER|\alpha, \beta) = \frac{\beta^{-\alpha} AER^{\alpha-1} e^{-\frac{AER}{\beta}}}{\Gamma(\alpha)} \tag{33}$$

Therefore, the F_E can be simplified as follows:

$$\begin{aligned} F_E &= \left[\sum \phi_{(z)}\left(P_E + P_{(z)}\right)\right] \times UF \times d_c \times f \times OP \\ &\times EC_{kg}(m_{BEB} + n \times lf \times m_p) \end{aligned} \tag{34}$$

where $\phi_{(z)}$ and $P_{(z)}$ represents the probability of recharging and the service fees charged respectively to the charging strategy z, respectively where $\phi_{(z)}$ can be determined by the number of chargers.

Eventually, the daily energy cost (DC_E) can be calculated as F_E divided by OP as shown below:

$$\begin{aligned} DC_E &= F_E \times \frac{1}{OP} \\ &= \left[\sum \phi_{(z)}\left(P_E + P_{(z)}\right)\right] \times UF \times d_c \times f \\ &\times EC_{kg}(m_{BEB} + n \times lf \times m_p) \end{aligned} \tag{35}$$

3.2.3.4 Implicit Cost

The implicit cost (C_N) for electric buses includes range anxiety cost (N_R), alternative vehicle cost (N_A) and repower annoyance cost (N_{RA}). N_R refers to the implicit cost of preparing another CB to back up in case any incidents happen. In other words, it quantifies the extra cost to be charged by the limited driving range since it cannot meet the user's travel demand. It can be calculated as below.

$$N_R = \max(0, (1 - PF)) \times RV \tag{36}$$

N_A measures the opportunity cost incurred when the powertrain cannot meet the travel demand. Essentially, it calculates the direct fuel cost charged on alternative transportation when the BEB is unable to fulfil the travel needs which can be computed as below:

$$N_A = P_F \times (AVKD - AVKT) \times FC \tag{37}$$

where P_F is fuel price, FC is the fuel consumption rate which it is influenced by the total mass of BEB. Therefore, the component of FC can be computed as below:

$$FC = FC_{kg}(m_{BEB} + n \times lf \times m_p) \tag{38}$$

where FC_{kg} is the fuel consumption rate per kg and is set at 0.001065L/km (Hao et al., 2022).

Upon simplifying, the final N_A is sorted out as below:

$$\begin{aligned} N_A &= P_F \times (AVKD - UF \times AVKD) \times FC_{kg}(m_{BEB} + n \times lf \times m_p) \\ &= P_F \times AVKD \times (1 - UF) \times FC_{kg}(m_{BEB} + n \times lf \times m_p) \\ &= P_F \times d_c \times f \times OP \times (1 - UF) \times FC_{kg}(m_{BEB} + n \times lf \times m_p) \end{aligned} \tag{39}$$

where $1 - UF$ represents the distance ratio covered by fossil fuels.

N_{RA} indicates the extra time cost when finding a charging station or queueing for and waiting for the charging infrastructure. It can be computed as below:

$$\begin{aligned} N_{RA} = Z_e \times t_c \times LC \times UF \times \frac{AVKD}{AER} + LC \times OP \\ \times \left(\phi_f \times DVKT \times UF \times \frac{EC}{PR_f} + \phi_S \times DVKT \times UF \times \frac{EC}{PR_S}\right) \end{aligned} \tag{40}$$

where t_c is the trip time to and from public charging stations, LC is the labour cost, PR_S and PR_f refer to the charging powers for slow charging and fast charging accordingly. Z_e is the travel annoyance multiplier, which is set to be 3.5. In other words, the extra psychological resistance to stress and distraction of a secondary refuelling trip due to loss aversion is 3.5 times higher than CB (Köbberling and Wakker, 2005; National Research Council, 2013). Upon simplifying, the component of N_{RA} can be obtained as shown below:

$$N_{RA} = Z_e \times t_c \times LC \times UF \times \frac{AVKD}{AER} + LC \times OP \tag{41}$$

$$\times \left(\sum \phi_{(z)} \times DVKT \times UF \times \frac{EC_{kg}(m_{BEB} + n \times lf \times m_p)}{PR_{(z)}} \right)$$

where $PR_{(z)}$ is where the charging powers of the charging strategy z. $DVKT$ can be further interpreted as below:

$$\begin{aligned} DVKT &= AVKT \times \frac{1}{OP} \\ &= UF \times AVKD \times \frac{1}{OP} \\ &= UF \times d_c \times f \times OP \times \frac{1}{OP} \\ &= UF \times d_c \times f \end{aligned} \tag{42}$$

Further simplifying, the component of N_{RA} can be finalized as below:

$$\begin{aligned} N_{RA} &= Z_e \times t_c \times LC \times UF \times \frac{d_c \times f \times OP}{AER} + LC \times OP \\ &\quad \times \sum (\phi_{(z)} \times UF \times d_c \times f \times UF \times \frac{EC_{kg}(m_{BEB} + n \times lf \times m_p)}{PR_{(z)}}) \\ &= Z_e \times t_c \times LC \times UF \times \frac{d_c \times f \times OP}{AER} + LC \times OP \\ &\quad \times UF \times d_c \times f \times \sum (\phi_{(z)} \times UF \times \frac{EC_{kg}(m_{BEB} + n \times lf \times m_p)}{PR_{(z)}}) \\ &= LC \times OP \times UF \times d_c \times f \times \left[\frac{Z_e \times t_c}{AER} \right. \\ &\quad \left. + \sum (\phi_{(z)} \times UF \times \frac{EC_{kg}(m_{BEB} + n \times lf \times m_p)}{PR_{(z)}}) \right] \end{aligned} \tag{43}$$

By integrating all the components, the total implicit cost (C_N) can be shown as below:

$$\begin{aligned} C_N &= N_R + N_A + N_{RA} \\ &= \max(0, (1 - PF) \times RV) \\ &\quad + P_F \times d_c \times f \times OP \times (1 - UF) \times FC_{kg}(m_{BEB} + n \times lf \times m_p) \\ &\quad + LC \times OP \times UF \times d_c \times f \times \left[\frac{Z_e \times t_c}{AER} + \sum (\phi_{(z)} \times UF \times \frac{EC}{PR_{(z)}}) \right] \\ &= \max(0, (1 - PF) \times RV) \\ &\quad + d_c \times f \times OP \times \left\{ P_F \times (1 - UF) \times FC_{kg}(m_{BEB} + n \times lf \times m_p) \right. \\ &\quad + LC \times OP \times UF \times d_c \times f \times \left[\frac{Z_e \times t_c}{AER} \right. \end{aligned} \tag{44}$$

$$+\sum(\phi_{(z)} \times UF \times \frac{EC_{kg}(m_{BEB} + n \times lf \times m_p)}{PR_{(z)}})\Bigg]$$

Ultimately, the daily implicit cost (DC_N) can be calculated by removing the BEB annual operating days. It can be computed as below:

$$\begin{aligned} DC_N = {} & \max(0, (1 - PF) \times RV) \\ & + d_c \times f \times \Big\{P_F \times (1 - UF) \times FC_{kg}(m_{BEB} + n \times lf \times m_p) \\ & + LC \times UF \times d_c \times f \times \Bigg[\frac{Z_e \times t_c}{AER} \\ & + \sum(\phi_{(z)} \times UF \times \frac{EC_{kg}(m_{BEB} + n \times lf \times m_p)}{PR_{(z)}})\Bigg] \end{aligned} \quad (45)$$

3.2.3.5 Maintenance and Repair Cost

The maintenance and repair cost (C_M) for vehicles can be categorised into two components: maintenance expenditure (M) and repair cost (R) as shown below:

$$C_M = M + R \quad (46)$$

The maintenance expenditure (M) is mostly influenced by the vehicle mileage and vehicle age. It can be obtained from the equation below:

$$\begin{aligned} M &= mc \times AVKT \\ &= mc \times UF \times AVKD \\ &= mc \times UF \times d_c \times f \times OP \end{aligned} \quad (47)$$

where the vehicle maintenance cost ratio (mc) is assumed to be 0.685 in comparison to CB.

The repair cost (R) for BEB reflects the battery replacement cost. It can be obtained from the equation below:

$$R = B_{size} \times (BC_{new} - BC_{old}) \quad (48)$$

where B_{size} is the new battery size, BC_{new} is the cost of a new battery, BC_{old} is the cost of an old battery. It is estimated that battery needs to be changed every 200,000km (SAE China, 2021).

The daily maintenance and repair cost (DC_M) can be calculated as C_M divided by OP as shown below:

$$\begin{aligned} DC_M &= (M + R) \times \frac{1}{OP} \\ &= mc \times UF \times d_c \times f + \frac{B_{size} \times (BC_{new} - BC_{old})}{OP} \end{aligned} \quad (49)$$

3.2.3.6 Taxes and Fees

The taxes and fees (C_T) include two elements: the tax on BEB (T) and highway tolls fare (G) as shown below:

$$C_T = T + G \tag{50}$$

The tax on BEB (T) refers to the vehicle purchase tax. And, the highway tolls (G) can be estimated by the $DVKT$ on the highway which can be computed as below:

$$G = u \times e \times OP \tag{51}$$

where u is the rate of highway tolls by BEB and e is the estimated $DVKT$ on the highway. By integrating all the components, the daily taxes and fees (DC_T) can be calculated as C_T divided by OP as shown below:

$$\begin{aligned} DC_T &= (T + G) \times \frac{1}{OP} \\ &= \frac{T}{OP} + u \times e \end{aligned} \tag{52}$$

In general, the model of $DPCO^{y,r}$ can be computed as follows:

$$DPCO^{y,r} = (DC_V + DC_I + DC_E + DC_N + DC_M + DC_T) \times q \tag{53}$$

3.3 Stage 2: Data Collection

The process of data collection is divided into five parts, with all data gathered online from various journals, articles, and reliable websites. The first part focuses on gathering detailed information about the specifications of the buses such as the type of bus, and passenger capacity. This part is important for understanding how each different design of bus interacts with environmental factors. It helps to evaluate the relationship between bus capacity, fuel or energy consumption, and environmental impacts, particularly in terms of emissions and consumption under different load conditions.

The second part involves collecting data on the characteristics of the bus routes. This includes the length of bus routes, and the gradient of slopes along the way. This section captures the geographic and environmental challenges that may influence the bus's performance. Elements like hilly terrain or longer routes can affect fuel efficiency, battery life, and overall operational effectiveness.

The third part addresses the characteristics of the charging systems for electric buses. This section focuses on the infrastructure available for recharging, including the location of charging stations and the time required for a full charge. It also examines how these factors impact fleet scheduling and operational efficiencies, such as the need to plan routes around charging stations or the downtime required for charging.

The fourth part examines the costs associated with bus insurance by collecting the data on various insurance policies available for the fleet, the premiums paid, and the coverage options. This data allows for a deeper analysis of the financial obligations involved in running a bus fleet, as insurance costs can have a significant long-term impact on the total operating costs and operational sustainability.

Lastly, the final part focuses on collecting additional constants that could affect the overall analysis of the bus fleet's performance. These constants include factors like the average number of operating days per year over ten years, and the residual value of the buses after 10 years of service. While these factors may seem marginal, they play a critical role in calculating long-term operational costs. These variables provide a more accurate and holistic assessment of fleet performance, helping to predict future costs and operational efficiency with greater precision.

3.4 Stage 3: Design of Survey Form

The perceptions and ratings of experts on the respective influential factors are crucial in shaping a sustainable and viable green fleet operating network for electric buses. As their opinions are important to be used as weightage in fuzzy TOPSIS analysis to determine the desirable bus routes for electric bus operations. As presented in Appendix A, a questionnaire was designed into two sections, Section 1: Expert Information and Section 2: Expert Perception. The first section contains eleven questions asking for basic personal information as the expert who participated is expected to have related relationships in the transportation field.

The second section aims to collect the ratings of experts on each influential factor. Two primary aspects, namely supply and demand are of utmost importance as described in Table 3.1. The supply aspect plays a key role in minimizing energy consumption, energy emissions, and cost for electric bus operations while the demand aspect targets maximizing passenger load factor. These four influencing factors are selected based on the parameters that affect the electrification of bus operations. They include vehicle and route-specific parameters (energy consumption and cost), environmental parameter (energy emissions), and operational parameter (passenger load factors) (Jahic et al., 2023).

Table 3.1: Influential Factors and Its Description.

Influential Factor		Description
Supply	Energy Consumption	It refers to the total energy used to support electric bus operations (including mechanical energy, auxiliary energy, and energy loss in the charging system).
	Energy Emissions	It indicates the carbon dioxide (CO_2) emissions generated by electric bus operations.
	Cost	It refers to the perceived cost of ownership (PCO) that encompasses the relevant expenses associated with the operations of electric buses (including vehicle cost, insurance cost, energy cost, implicit cost, maintenance & repair costs, and taxes & fees).
Demand	Passenger Load Factor	It denotes the capacity utilization of electric buses (percentage of total number of onboard bus passengers).

The experts are required to quantify the importance (weightage) of the respective factor in determining desirable bus routes for electric bus operations. Later, they are required to choose the relevant scale (linguistic term) in accordance with the expert perception of the anticipated importance (weightage) of each influential factor in operating electric buses. Table 3.2 shows the rating scales from 1 to 5 where a higher value of scale signifies greater importance (weightage) of the influential factor in operating electric buses.

Table 3.2: Rating Scale with Linguistic Terms.

Scale	Linguistic Term
1	Very Low
2	Low
3	Moderate
4	High
5	Very High

3.5 Stage 4: Conduct of Survey Form

The conduct of survey aims to gather opinions from experts who specialize in the transportation field, either with extensive experience in the industry or a strong educational background in environmental sustainability or green transportation. The survey starts by selecting respondents from both academic and non-academic backgrounds to ensure a balanced representation. The academic participants consist of lecturers from UTAR Sungai Long, while the non-academic participants are from UTAR's Department of General Services. Once the target respondents are identified, the questionnaires are sent via Gmail. However, for some respondents requiring in-depth interviews, these were conducted face-to-face. The responses are then collected and organized in Microsoft Excel.

3.6 Stage 5: Fuzzy TOPSIS

This project aims to adopt fuzzy TOPSIS to select the most desirable bus route based on environmental and cost aspects. According to Nădăban, Dzitac and Dzitac (2016), the ten-step fuzzy TOPSIS can be carried out as below:

Step 1. Assign the linguistic terms to the alternatives and criteria.

Consider a decision-making group with P members, the linguistic terms ($\tilde{x}_{rj}^{p}$) in terms of five categories (very low, low, average, high and very high) of the p^{th} decision-maker matrix about the alternatives (bus route r) against criteria (influential factor j) can be denoted by the decision-making matrix D_{rj}^{p} as below:

$$D_{rj}^{p} = \begin{bmatrix} \tilde{x}_{11}^{p} & \tilde{x}_{12}^{p} & \cdots & \tilde{x}_{1j}^{p} \\ \tilde{x}_{21}^{p} & \tilde{x}_{22}^{p} & \cdots & \tilde{x}_{2j}^{p} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{r1}^{p} & \tilde{x}_{r2}^{p} & \cdots & \tilde{x}_{rj}^{p} \end{bmatrix} \tag{54}$$

Step 2. Define the weightage of criteria.

The weightage of criteria denotes the importance of that particular criterion in comparison to the others. Eventually, it reflects the degree of influence each criterion has on the overall decision. The weightage given by p^{th} decision maker is denoted by:

$$\widetilde{w}_{j}^{p} = \left(w_{1}^{p}, w_{2}^{p}, \cdots, w_{j}^{p}\right) \tag{55}$$

Step 3. Assign the fuzzy number set to the linguistic terms and weightage.

Each $\tilde{x}_{rj}^{p}$ provided by p^{th} decision maker is allocated fuzzy number $\left(a_{rj}^{p}, b_{rj}^{p}, c_{rj}^{p}\right)$ based on the conversion outlined in Table 3.1. The D_{rj}^{p} has then become:

$$D_{rj}^{p} = \begin{bmatrix} \tilde{x}_{11}^{p} & \tilde{x}_{12}^{p} & \cdots & \tilde{x}_{1j}^{p} \\ \tilde{x}_{21}^{p} & \tilde{x}_{22}^{p} & \cdots & \tilde{x}_{2j}^{p} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{r1}^{p} & \tilde{x}_{r2}^{p} & \cdots & \tilde{x}_{rj}^{p} \end{bmatrix} \text{where } \tilde{x}_{rj}^{p} = \left(a_{rj}^{p}, b_{rj}^{p}, c_{rj}^{p}\right) \tag{56}$$

Table 3.3: Triangular Fuzzy Number (Nădăban, Dzitac and Dzitac, 2016).

Linguistic Term, $\tilde{x}_{rj}^{p}$	Fuzzy Number, $\left(a_{rj}^{p}, b_{rj}^{p}, c_{rj}^{p}\right)$
Very Low	(1,1,3)
Low	(1,3,5)
Average	(3,5,7)
High	(5,7,9)
Very High	(7,7,9)

Step 4. Determine the combined fuzzy decision-making matrix.

For every p, the aggregated fuzzy rating $\tilde{x}_{rj} = \left(a_{rj}, b_{rj}, c_{rj}\right)$ of D_{rj}^{p} can be obtained as below:

$$a_{rj} = \min_{p}\left\{a_{rj}^{p}\right\} \quad , \quad b_{rj} = \frac{1}{P}\sum_{p=1}^{P} b_{rj}^{p} \quad , \quad c_{rj} = \max_{p}\left\{c_{rj}^{p}\right\} \tag{57}$$

The aggregated fuzzy weight of the criterion C_j is denoted by:

$$\widetilde{w}_j = \left(w_1, w_2, \cdots, w_j\right) \tag{58}$$

where

$$w_{j1} = \min_{p}\left\{w_{j1}^{p}\right\} \quad , \; w_{j2} = \frac{1}{P}\sum_{p=1}^{P} w_{j2}^{p} \quad , \; w_{j3} = \max_{p}\left\{w_{j3}^{p}\right\} \tag{59}$$

Step 5. Establish the normalized fuzzy decision-making matrix.

The normalized fuzzy decision-making matrix ($\widetilde{N}$) can be formed as below:

$$\widetilde{N} = \begin{bmatrix} \tilde{n}_{11} & \tilde{n}_{12} & \dots & \tilde{n}_{1j} \\ \tilde{n}_{21} & \tilde{n}_{22} & \dots & \tilde{n}_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{n}_{r1} & \tilde{n}_{r2} & \dots & \tilde{n}_{rj} \end{bmatrix} \tag{60}$$

For benefit criteria, $\tilde{n}_{rj}$ can be expressed as below:

$$\tilde{n}_{rj} = \left(\frac{a_{rj}}{c_j^{+}}, \frac{b_{rj}}{c_j^{+}}, \frac{c_{rj}}{c_j^{+}}\right) \text{ where } c_j^{+} = \max_{r}\left\{c_{rj}\right\} \tag{61}$$

For cost criteria, $\tilde{n}_{rj}$ can be expressed as below:

$$\tilde{n}_{rj} = \left(\frac{a_j^{-}}{c_{rj}}, \frac{a_j^{-}}{b_{rj}}, \frac{a_j^{-}}{a_{rj}}\right) \text{ where } a_j^{-} = \min_{r}\left\{a_{rj}\right\} \tag{62}$$

Step 6. Establish the weighted normalized fuzzy decision-making matrix.

The weighted normalized matrix fuzzy decision-making matrix ($\tilde{V}$) can be expressed as below:

$$\begin{aligned} \tilde{V} &= \widetilde{N} \times \widetilde{w}_j \\ &= \begin{bmatrix} \tilde{n}_{11} & \tilde{n}_{12} & \dots & \tilde{n}_{1j} \\ \tilde{n}_{21} & \tilde{n}_{22} & \dots & \tilde{n}_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{n}_{r1} & \tilde{n}_{r2} & \dots & \tilde{n}_{rj} \end{bmatrix} \times \left(w_1, w_2, \cdots, w_j\right) \end{aligned}$$

$$= \begin{bmatrix} \tilde{v}_{11} & \tilde{v}_{12} & \cdots & \tilde{v}_{1j} \\ \tilde{v}_{21} & \tilde{v}_{22} & \cdots & \tilde{v}_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{v}_{r1} & \tilde{v}_{r2} & \cdots & \tilde{v}_{rj} \end{bmatrix} \tag{63}$$

Step 7. Calculate the Fuzzy Positive Ideal Solution and Fuzzy Negative Ideal Solution.

The Fuzzy Positive Ideal Solution (FPIS) chooses the highest $\tilde{v}_{rj}$ across all criteria j, indicating the most desirable combination of j while Fuzzy Negative Ideal Solution (FNIS) chooses the lowest $\tilde{v}_{rj}$ across all criteria j, indicating the least desirable combination of j.

Correspondingly, FPIS can be expressed as below:

$$A^{+} = (\tilde{v}_1^{+}, \tilde{v}_2^{+}, \cdots, \tilde{v}_n^{+}) \text{ where } \tilde{v}_j^{+} = \max_r \{v_{rj3}\} \tag{64}$$

And, FNIS can be expressed as below:

$$A^{-} = (\tilde{v}_1^{-}, \tilde{v}_2^{-}, \cdots, \tilde{v}_n^{-}) \text{ where } \tilde{v}_j^{-} = \min_r \{v_{rj1}\} \tag{65}$$

Step 8. Calculate the distance from each alternative to the FPIS and FNIS.

The distance of each bus route r to A^{+} is used to assess the extent of positive solution while the distance of each bus route r to A^{-} is used to assess the extent of the negative solution.

By considering the following:

$$\tilde{v}_{rj} = (a_1, b_1, c_1),\ \tilde{v}_j^{+} = (a_2, b_2, c_2),\ \tilde{v}_j^{-} = (a_3, b_3, c_3) \tag{66}$$

The distance between each criterion j to the FPIS can be obtained as follows:

$$d(\tilde{v}_{rj}, \tilde{v}_j^{+}) = \sqrt{\frac{1}{3}[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2]} \tag{67}$$

And, the distance from each bus route i to FPIS can be computed as below:

$$d_r^{+} = \sum_{j=1}^{n} d(\tilde{v}_{rj}, \tilde{v}_j^{+}) \tag{68}$$

Similarly, the distance between each criterion j to the FNIS can be obtained as follows:

$$d(\tilde{v}_{rj}, \tilde{v}_j^{-}) = \sqrt{\frac{1}{3}[(a_1 - a_3)^2 + (b_1 - b_3)^2 + (c_1 - c_3)^2]} \tag{69}$$

And, the distance from each bus route i to FNIS can be computed as below:

$$d_r^- = \sum_{j=1}^{n} d\left(\tilde{v}_{rj}, \tilde{v}_j^-\right) \tag{70}$$

Step 9. Calculate the closeness coefficient for each alternative.

The closeness coefficient (CC_r) ranges from 0 to 1 in which a higher value indicate that the bus route r is more beneficial with lower cost. On the other hand, lower values of CC_r suggest that bus route r offers fewer benefits at higher cost. The component of CC_r can be determined as below:

$$CC_r = \frac{d_r^-}{d_r^- + d_r^+} \tag{71}$$

Step 10. Rank the bus route r.

Order the CC_r from highest to lowest value. The highest CC_r indicates the bus route r is the most desirable to implement bus electrification.

3.7 Summary

In summary, this chapter has successfully developed a viable framework proposing a multi-criteria green fleet planning approach. Initially, it estimates the energy consumption, energy emissions, PCO associated with BEBs and passenger load factor across numerous bus routes. Next, the fuzzy TOPSIS approach incorporates influential criteria (energy consumption, emissions and cost) to rank each bus route based on its suitability for electrification. To complete the fuzzy TOPSIS analysis, a survey form must be designed for experts to give ratings on each criterion. The purpose of this survey form is to collect the weightage of each criterion which allows the fuzzy TOPSIS approach to effectively evaluate and identify the most desirable candidate for electrification among all the bus routes. Overall, this proposed methodology encourages the development of green energy public bus transportation, with strategies respond to tackle the environmental vulnerabilities and authority's needs.

CHAPTER 4

AN ILLUSTRATIVE CASE STUDY

4.1 Introduction

This chapter analysed an illustrative case study to assess the viability of the proposed methodology for a viable multi-criteria green fleet planning in supporting BEB operations. It begins with the data description that includes an analysis of the expert survey. Then, the fuzzy TOPSIS analysis is presented in two parts: the first part focuses on determining the most desirable bus route for BEB operations, while the second part evaluates the most suitable bus type for BEB operations on each route. Finally, further analysis is performed to explore the aspect of influential factors with the corresponding weightage (importance level) on the resultant findings.

4.2 Data Description

After collecting all the data, each aspect is described in this section. This includes descriptions of bus specifications and bus route characteristics, followed by the characteristics of charging systems and bus insurance costs. Finally, the section ends with a description of additional important constants.

4.2.1 Bus Specifications

A total of 11 BEBs have been selected from different countries as the potential bus to be adopted. As presented in Table 4.1, the basic specifications (manufacturer, mass of empty BEB, passenger capacity, frontal area, and all-electric range) of each BEB type along with their respective labels are listed.

Table 4.1: Basic Specifications of Each BEB Type.

Label	BEB Type	Manufacturer	m_{BEB} (kg)	n	a (km^2)	AER (km)	Reference
Y1	BYD eBus B13	China	17417.95	45	8.415	455	BYD (2024)
Y2	Switch Metrocity	England	13000	36	7.0395	305.775	SWITCH (2024a)
Y3	Pelican Yutong e9	UK	9750	24	7.9739	313.822	Pelican (2024a)
Y4	Pelican Yutong e10	UK	13200	33	8.3768	400	Pelican (2024b), Yutong (2021)
Y5	Pelican Yutong e12	UK	13750	39	8.4915	370	Pelican (2024c), Pelican (2024d)
Y6	Pelican Yutong TCe12	UK	13500	50	8.67	321.869	Deakin (2019), Pelican (2024e)
Y7	Switch e1	Europe	10775	28	7.75	390	Deakin (2019), SWITCH (2024b)
Y8	Go Auto Azure (10.5)	Malaysia	11800	26	8.375	270	GOAUTO (2024a)
Y9	Go Auto G-Bus	Malaysia	12000	37	9.2	200	GOAUTO (2024b)
Y10	Go Auto Azure (12)	Malaysia	13000	42	8.375	400	GOAUTO (2024c)
Y11	EBIM (Sync R&D)	Malaysia	17000	17	8.0825	200	Pertz (2019)

Other than that, the auxiliary power considered is determined in two components and summarized in Table 4.2. The first component, which varies based on the length of the BEB, includes energy usage for systems such as lamps, passenger information displays, air compressors, hydraulic pumps, air conditioning, and heating systems. The second component, which is assumed to be consistent across all BEB types, such as energy usage related to the steering pump, doors, parking brakes, and wipers.

Table 4.2: Auxiliary Power of BEBs.

System	Auxiliary Power (kW)	Reference
Lamps	1.6883-2.2125	Basma et al. (2022)
Passenger Information Systems	2.235-3.3186	
Air compressor	4.47-6.6375	
Hydraulic pump	2.98-4.425	
Air condition	2.98-4.425	
Heating	21.1042-34.89	
Steering Pump	0.7225	Bartłomiejczyk and Kołacz (2020)
Doors	0.09	
Parking Brakes	0.56	
Wipers	0.5	

Considering that vehicle prices vary across different regions and countries the analysis considered the cost of BEBs based on their manufacturing country as listed in Table 4.3.

Table 4.3: Vehicle Price.

Manufacturer	VP (RM)	Reference
China	1,800,000	Bernama (2023)
Europe	2,500,000	
Malaysia	1,000,000	ACS (2024)

Besides, the battery replacement cost that reflects the repair cost (R) for BEB is set to be RM 728,072 (The Star, 2023).

4.2.2 Bus Route Characteristics

This project examines the applicability of the proposed methodology for Universiti Tunku Abdul Rahman (UTAR), Sungai Long campus. UTAR, a private university, provides six shuttle bus services that are available on weekdays except public holidays, with varying frequencies across each route as detailed in Appendix B. Each bus route charges RM1 per trip for students and features multiple bus stops along its route. They depart separately from UTAR terminal and follow distinct routes to pick up students who reside far from campus (Universiti Tunku Abdul Rahman, 2019). The UTAR bus route maps are illustrated in Appendix C. Google Maps was incorporated to visualize the actual bus routes and accurately obtain the bus route length covered and trip time. The relevant bus route characteristics are summarized in Table 4.4 below.

Table 4.4: UTAR Bus Route Characteristics.

Bus Route	f	d_c (km)	t (min)	UF	PF	Reference
Route-1	10	7	17	0.4496	0.7	Duoba (2013), Hao et al. (2021), Universiti Tunku Abdul Rahman (2019)
Route-2	10	8.3	19	0.5184	0.8	
Route-3	8	6.9	19	0.3558	0.6	
Route-4	8	9	22	0.4640	0.7	
Route-5	7	25.2	38	0.8915	1	
Route-6	8	11.1	11.1	0.5531	0.9	

Table 4.5 below listed the input value for the parameters used to calculate the energy consumption.

Table 4.5: Basic Bus Route Characteristics.

Parameter	Value	Reference
η	0.9	Asamer et al. (2016)
m_p	62.65kg	Azmi et al. (2009)
C_r	0.012	Wargula, Wieczorek and Kukla (2019)
k	1.2kg/m^3	Al-Ogaili et al. (2021)
C_d	0.645	Bayındırlı and Çelik (2018)
v_c	66.2 km/h	Ahmad et al. (2017)

Furthermore, Google Earth Pro was used here to visualize the actual bus routes and collect the slope data for each. Python programming was then used to calculate the mechanical energy required for each route. The detailed Python code can be found in Appendix D. A positive slope angle indicates that acceleration is needed to climb uphill, a negative slope angle suggests that deceleration is required to control the descent, and a relatively flat slope indicates the bus is maintaining a constant speed. The detailed slope data for each route can be found in Appendix E.

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4.2.3 Charging Systems Characteristics

The search for electric vehicle charging stations was conducted using platforms from ChargeSini (2024) and ChargeEV (2024). A total of ten charging stations closest to UTAR Sungai Long were selected for consideration. The locations of charging stations are visualized in Appendix F. This project considers two types of charging: slow and fast. Charging powers less than 22 kW were classified as slow charging, while those above 22 kW were considered fast charging (Wong, 2022). Since each charging station offers different types and numbers of charging piles with varying power outputs. Therefore, the parameters for analysis for each charging type were taken average across all ten different locations. In addition, the number of slow and fast charging piles was used to determine the probability of recharging using a public charger. The detailed characteristics of each charging stations is tabulated in Appendix G. Upon derived from the calculations mentioned above, the basic features of the charging station are detailed in Table 4.6.

Table 4.6: Charging Station Characteristics.

Parameter		Value	Reference
$\phi_{(z)}$	ϕ_S	0.7	ChargeSini (2024), ChargeEV (2024)
	ϕ_f	0.3	
$PR_{(z)}$	PR_S	17.2971 kW	
	PR_F	34.5 kW	
$P_{(z)}$	$P_{(S)}$	1.0371 (RM/kW)	
	$P_{(F)}$	1.3925 (RM/kW)	
t_c		24.3 mins	

As presented in Figure 3.3, the process of charging a BEB involves three critical stages. Initially, the energy resource undergoes voltage regulation by passing through a transformer, which is assumed to step down the voltage from 480V to 240V. Once the voltage is adjusted, the electricity is directed into the charging station, where it is temporarily stored within a high-capacity converter and assumed to have a power rating of 300kW. The final stage of the process involves the electricity transmission through a charging cable, which is securely connected to the BEB and set to be 11V. With the assumption made above, the power losses on the output terminals of the power supply system were summarized in Table 4.7.

Table 4.7: The Power on The Output Terminals of The Power Supply System.

Output Terminal		Charging Type		Reference
		Slow (kW)	Fast (kW)	
P_T	P_{cable}	0.0495	0.1035	Suruhanjaya Tenaga (n.d.)
	P_{trans}	0.43805	0.352	Apostolaki-Iosifidou, Codani and Kempton (2017)
	P_{ped}	19.5975	9.9338	

To determine the power losses in charging stations, it is essential to evaluate the efficiency of each component within the transmission system. The efficiencies of these elements are detailed in Table 4.8.

Table 4.8: The Efficiency of The Element of The Transmission System.

Parameter		Value	Reference
η_i	P_{cable}	0.95	Ryan (2024)
	P_{trans}	0.95	Unacademy (2022)
	P_{ped}	0.9	Mikhaylov, Tervonen and Fadeev (2012)

4.2.4 Bus Insurance Cost

Since the liability insurance is determined by the bus size and passenger accident insurance depends on the number of seats, the liability insurance, I_L is categorized into three different categories according to the bus size while the passenger accident insurance, I_A is set to be RM 50 per seat (Hao et al., 2022).

The specific details for each category of liability insurance cost are provided in Table 4.9.

Table 4.9: Liability Insurance Cost.

Bus Size (seats)	Cost (RM)	Reference
10-20	1620.80	Hao et al. (2022)
20-36	2343.25	
Over 36	2437.50	

Table 4.10 listed some other additional parameters for data analysis. The residual value of BEBs is assumed to be consistent at 10 years for all types. Electricity and fuel consumption rates, as well as maintenance cost ratios, are assumed to be the same across all BEB types. Annual operating days for buses are averaged from 2020 to 2025 to determine the operating days per year. Besides, fuel prices are based on Malaysia’s diesel price as of July 2024, and school bus driver labour costs are calculated from the average base salary in Malaysia on a per-day basis.

Table 4.10: Additional Important Constants.

Parameter	Value	Reference
rv_{10}	0.2652 unit	Hao et al. (2022)
EC	0.0024 kW/km	
FC	0.001065 L/km	
mc	0.685 RM/km	
OP	246 days	David (2020), David (2021), David (2022), David (2023) David (2024), and David (2025)
P_F	RM 3.35/L	RinggitPlus (2024)
LC	RM 112.90	Salary Expert (2024)
T	RM 0	JPJ (2024)

4.3 Expert Survey Analysis

As detailed in Table 4.11, all six experts possess distinguished educational backgrounds in transportation, specializing in areas such as fleet planning, management, and production. Their rich working experience in the transportation sector, whether through professional practice or academic study, provides a robust foundation for their contributions to the weightage ratings.

Table 4.11: Summary of Expert's Profile.

Expert	Position/Title	Area of Expertise	Years of Working	Highest Academic Qualifications
1	Manager	• Electric Bus • Public Transport Route and Fleet Planning • Production Planning and Management	19	Master
2	Assistant Manager	• Bus Booking • Bus Maintenance	16	Degree
3	Senior Assistant Manager	Logistic and Mailing	11	Master
4	Lecturer	Transportation	13	Master
5	Professor	Transportation	20	PhD
6	Professor	Transportation	7	PhD

The experts' ratings are summarized in Table 4.12, covering four key factors: energy consumption, energy emissions, PCO, and passenger load factor. Energy consumption was rated with a generally high level of importance, though one scale received the lowest rating. In contrast, energy emissions were mostly rated at a lower importance level, with only two experts assigning it high importance. Moreover, majority of experts supports PCO as the highest priority among the four criteria, with three experts rating it as very high, two as high, and only one giving it an average rating. Lastly, the passenger load factor received an overall above-average rating, with three experts marking it as average and three as high.

Table 4.12: Summary of Expert's Perception.

Expert	Energy Consumption (GW)	Energy Emissions (GW)	PCO (RM)	Passenger Load Factor
1	High	High	Average	High
2	High	Low	High	Average
3	Very Low	Very Low	Very High	Average
4	High	High	Very High	Average
5	High	Low	High	High
6	Average	Low	Very High	High

4.4 Fuzzy TOPSIS Analysis in Determining the Desirable Bus Route for BEB Operations

The first part of the fuzzy TOPSIS analysis identifies the most suitable bus route for BEB operations based on varying daily passenger loads (25%, 50%, 75%, or 100%) and charging strategies (slow or fast), as presented in Figure 4.1. The analysis then examines the relationship between CC and ranking of bus route based on four scenarios. The first scenario (scenario 1) focuses on individual cases at 25%, 50%, 75%, and 100% daily passenger loads with either slow or fast charging strategies. The second scenario (scenario 2) considers across all daily passenger loads with either slow or fast charging strategies. The third scenario (scenario 3) evaluates each 25%, 50%, 75%, or 100% daily passenger load with both charging strategies. Finally, the last scenario (scenario 4) presents a general analysis considering all daily passenger loads with both charging strategies. Since 11 BEBs are being evaluated, each produces different ranking of bus routes. Therefore, all the different result are combined and averaged to obtain the final overall ranking.

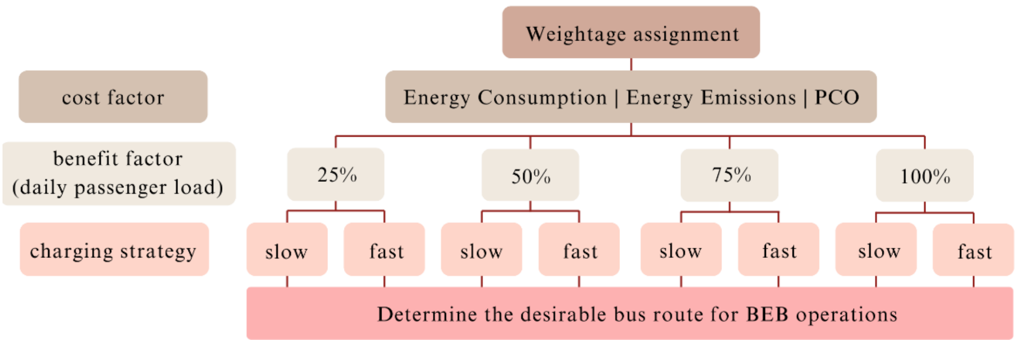


Figure 4.1: Overview of fuzzy TOPSIS Framework in Determining the Desirable Bus Route for BEB Operations.

4.4.1 Scenario 1: 25%, 50%, 75%, or 100% Daily Passenger Loads with Either Slow or Fast Charging Strategies

Table 4.13 presented altogether 8 different operating scenarios for data analysis purposes by considering varying daily passenger loads with different charging strategies.

Table 4.13: Scenarios of Varying Daily Passenger Loads with Different Charging Strategies and Corresponding Figures Listed.

Scenario	Figure
25% Daily Passenger Load with Slow Charging Strategy	Figure 4.2
25% Daily Passenger Load with Fast Charging Strategy	Figure 4.3
50% Daily Passenger Load with Slow Charging Strategy	Figure 4.4
50% Daily Passenger Load with Fast Charging Strategy	Figure 4.5
75% Daily Passenger Load with Slow Charging Strategy	Figure 4.6
75% Daily Passenger Load with Fast Charging Strategy	Figure 4.7
100% Daily Passenger Load with Slow Charging Strategy	Figure 4.8
100% Daily Passenger Load with Fast Charging Strategy	Figure 4.9

From Figure 4.2 to Figure 4.9 it could be seen that all the analysed scenarios reveal a similar finding in which it is clear that Route-1 scores the highest CC, indicates that it is the most likely candidate for electrification, followed by Route-2 with slightly higher CC than Route-3 which places third place. Later, Route-4 with CC around 0.55 ranks in fourth place. Moreover, Route-6 and Route-5 occupy the bottom two spots, with Route-5 being the least favourable for electrification due to the lowest CC.

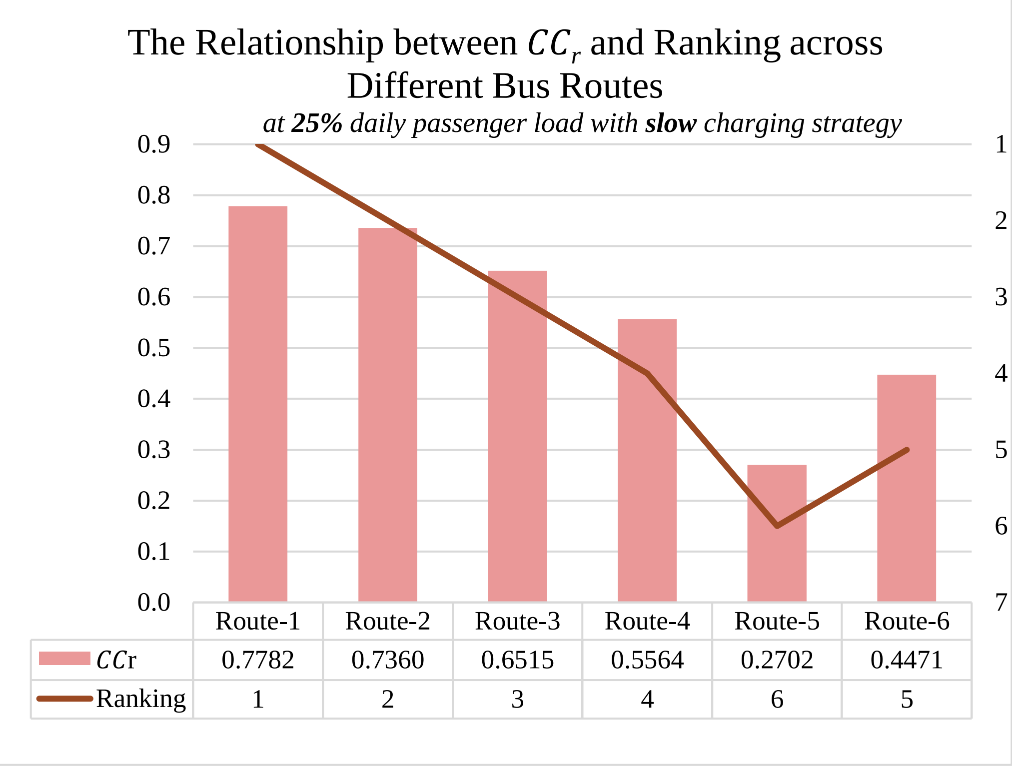


Figure 4.2: The Relationship Between CC_r and Ranking across Different Bus Routes at 25% Daily Passenger Load with Slow Charging Strategy.

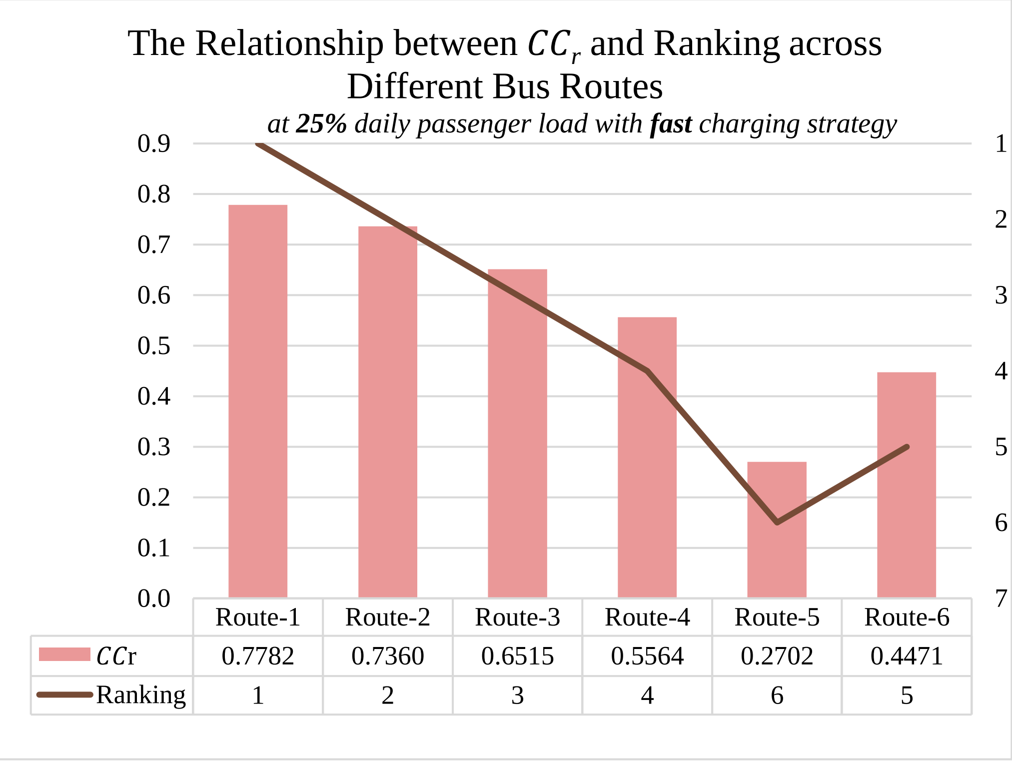


Figure 4.3: The Relationship Between CC_r and Ranking across Different Bus Routes at 25% Daily Passenger Load with Fast Charging Strategy.

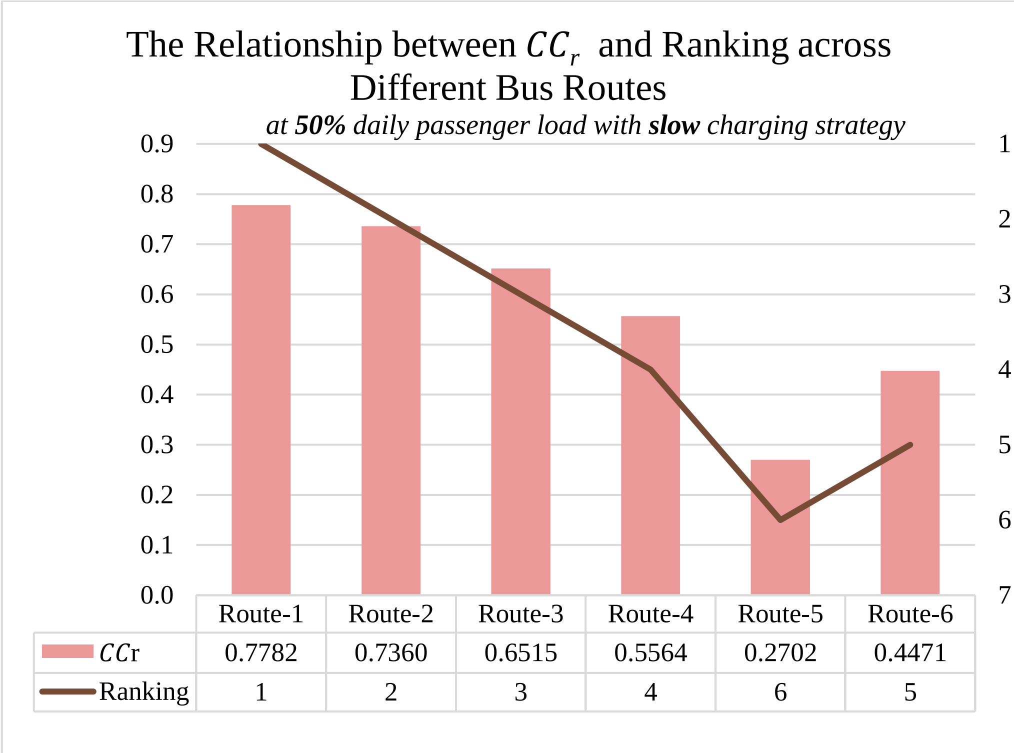


Figure 4.4: The Relationship Between CC_r and Ranking across Different Bus Routes at 50% Daily Passenger Load with Slow Charging Strategy.

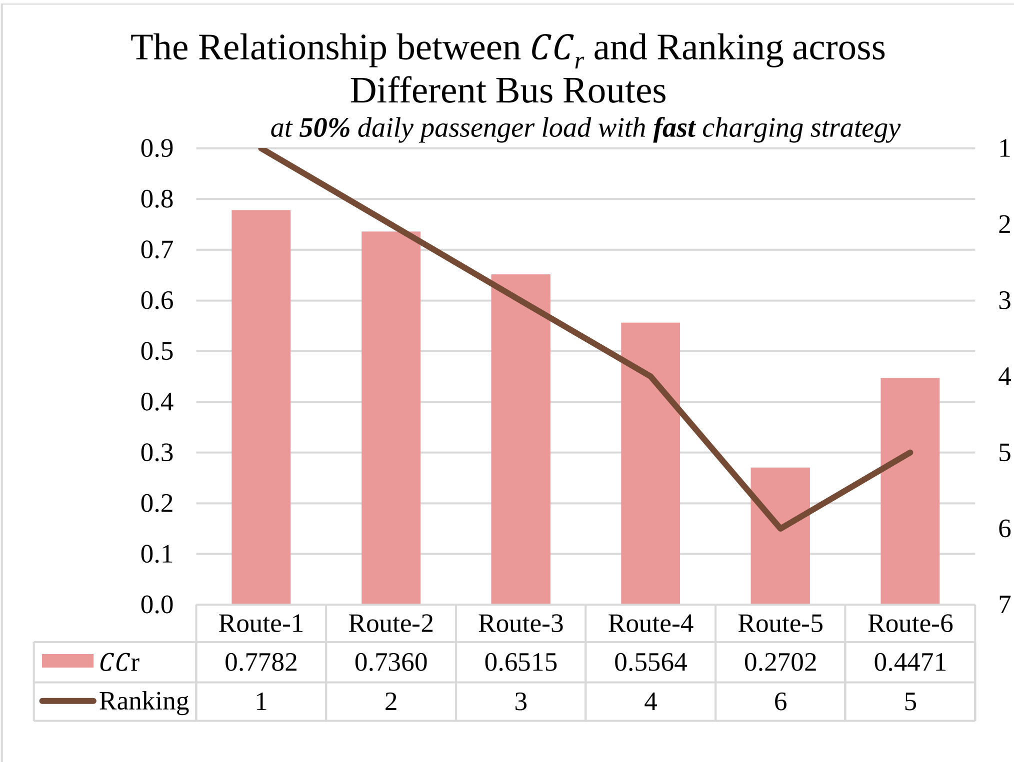


Figure 4.5: The Relationship Between CC_r and Ranking across Different Bus Routes at 50% Daily Passenger Load with Fast Charging Strategy.

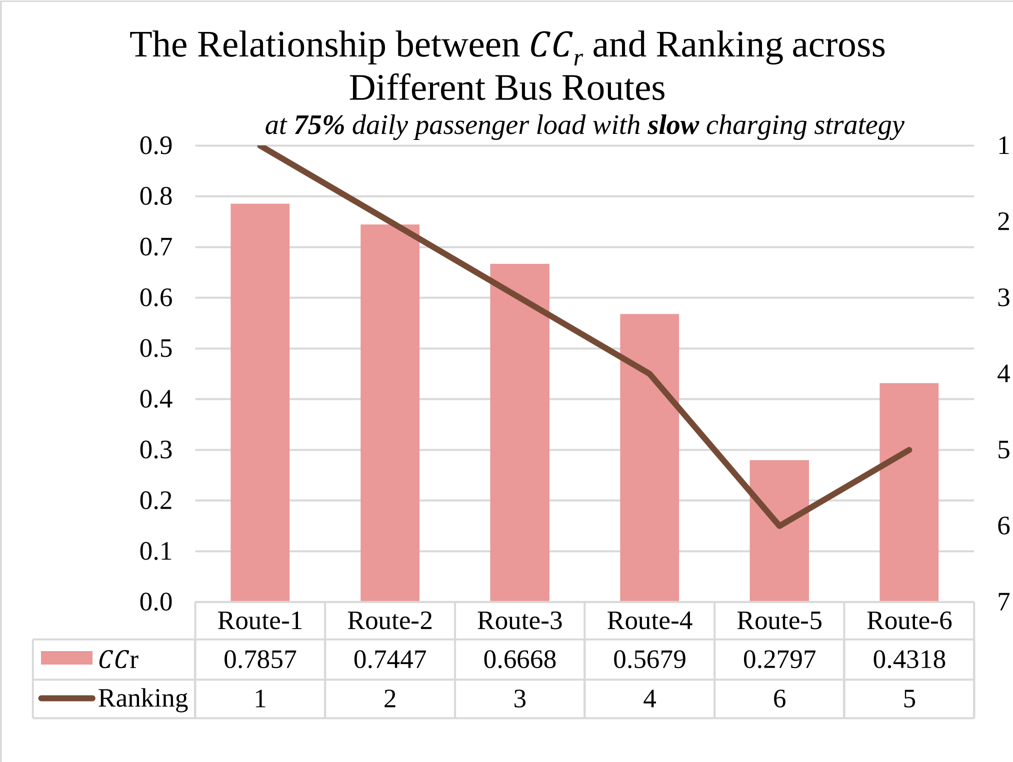


Figure 4.6: The Relationship Between CC_r and Ranking across Different Bus Routes at 75% Daily Passenger Load with Slow Charging Strategy.

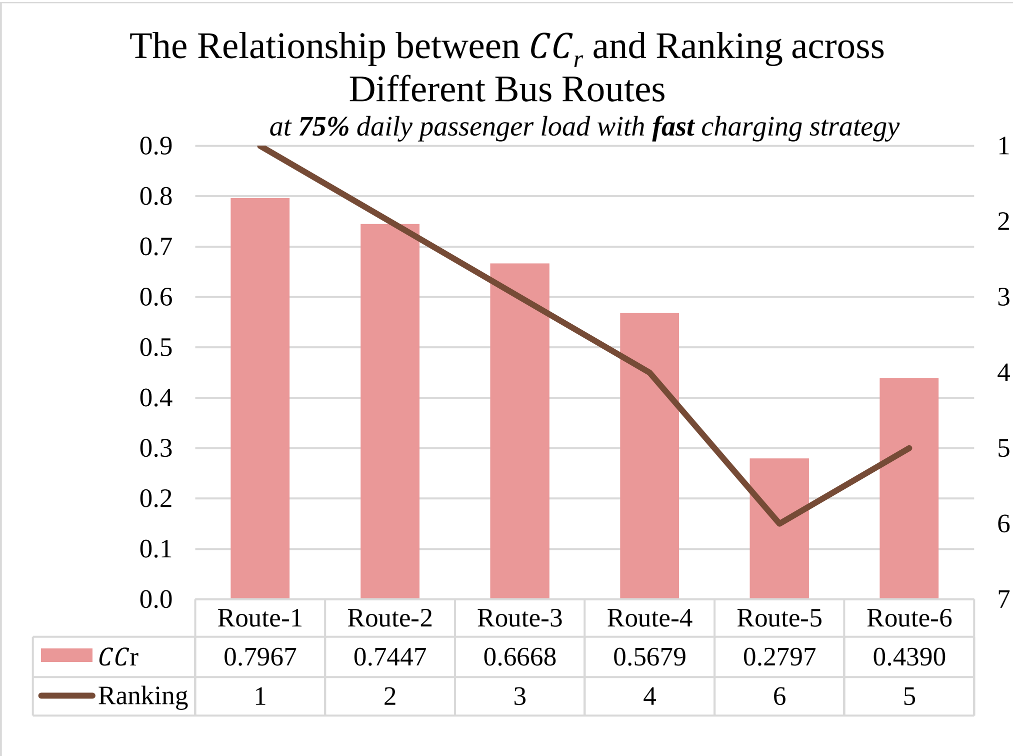


Figure 4.7: The Relationship Between CC_r and Ranking across Different Bus Routes at 75% Daily Passenger Load with Fast Charging Strategy.

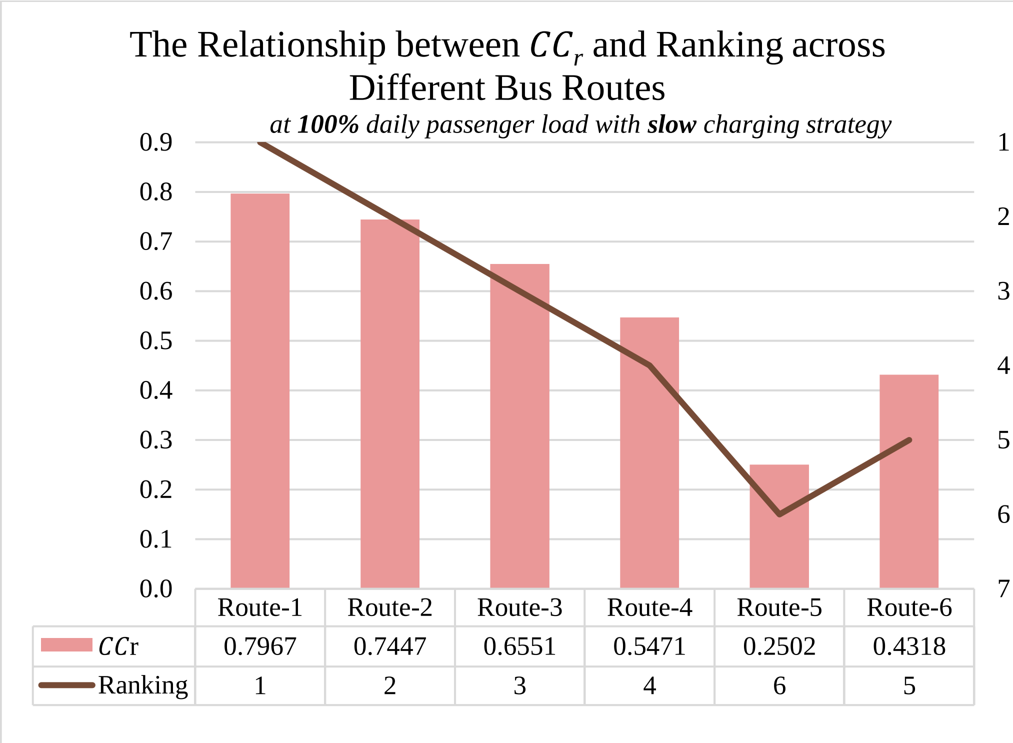


Figure 4.8: The Relationship Between CC_r and Ranking across Different Bus Routes at 100% Daily Passenger Load With Slow Charging Strategy.

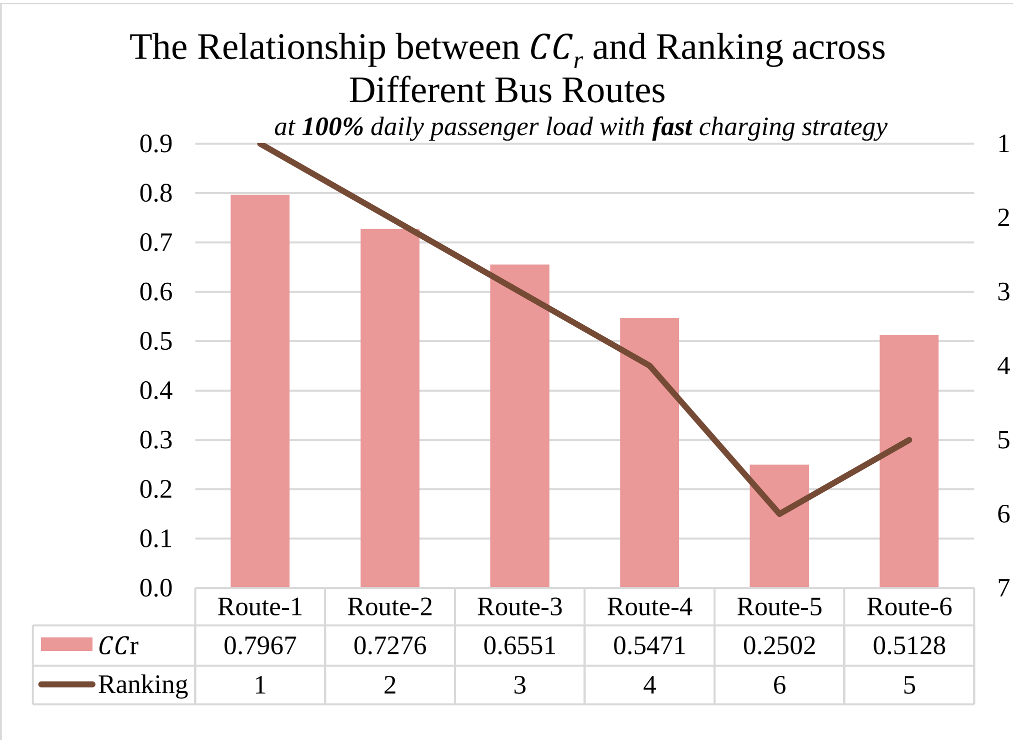
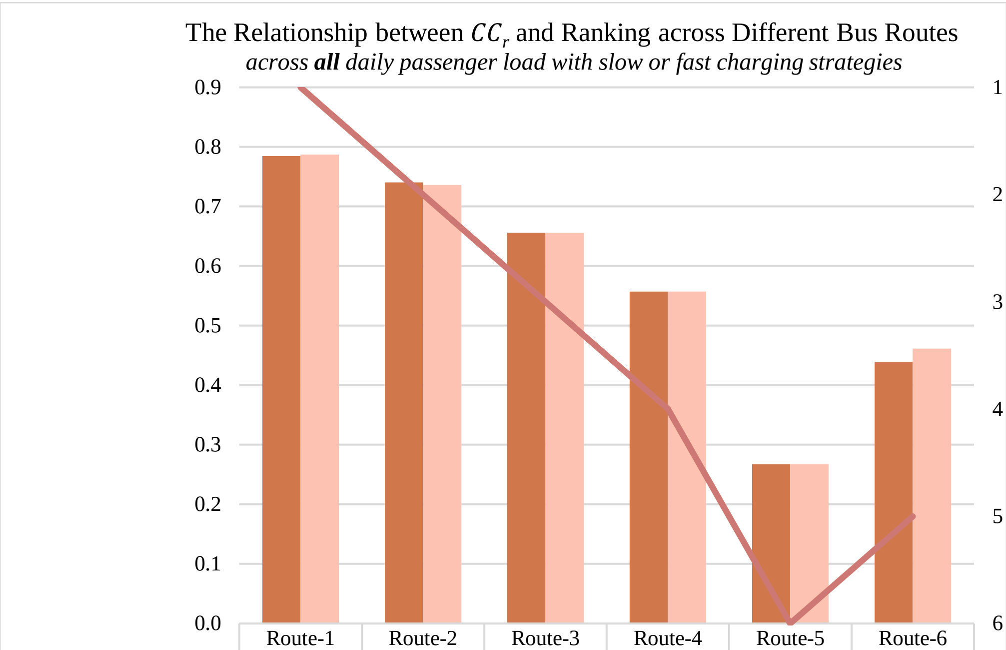


Figure 4.9: The Relationship Between CC_r and Ranking across Different Bus Routes at 100% Daily Passenger Load With Fast Charging Strategy.

4.4.2 Scenario 2: Across All Daily Passenger Loads with Either Slow or Fast Charging Strategies

The analysis under this scenario was conducted across all daily passenger loads by aggregating the results from Scenario 1 and focusing solely on the impact of the charging strategy. As illustrated in Figure 4.10, slow and fast charging strategies across all daily passenger loads exhibit similar ranking trends. Route-1 consistently scores the highest CC, indicating it remains the most likely candidate for electrification. Route-2 maintains the second-highest CC scores and ranks second, while Route-3 ranks third with the third-highest CC. For the fourth place and below, the CC scores and rankings are consistent across either charging strategies with the order being Route-4, Route-6, and Route-5.



	Route-1	Route-2	Route-3	Route-4	Route-5	Route-6
CCr (Slow)	0.7847	0.7403	0.6562	0.5570	0.2676	0.4395
CCr (Fast)	0.7874	0.7361	0.6562	0.5570	0.2676	0.4615
Ranking (Slow)	1	2	3	4	6	5
Ranking (Fast)	1	2	3	4	6	5

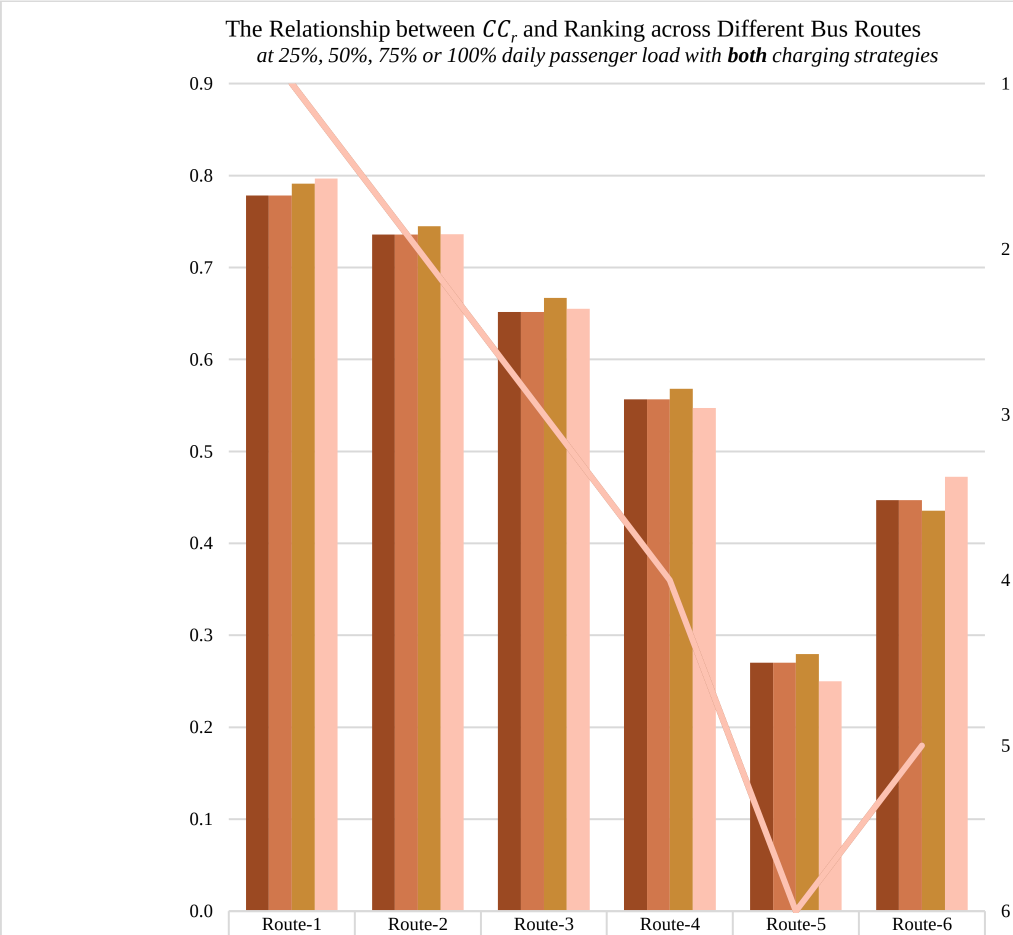
Figure 4.10: The Relationship Between CC_r and Ranking across Different Bus Routes across All Daily Passenger Loads with Either Slow or Fast Charging Strategies.

4.4.3 Scenario 3: 25%, 50%, 75%, or 100% Daily Passenger Load With Both Charging Strategies

Further analysis was conducted to examine each daily passenger load with both charging strategies to better understand the rankings for each route in different scenarios. In this analysis, the average of both charging strategies was considered as the sole charging type. As illustrated in Figure 4.11, the rankings for 25%, 50%, 75%, and 100% daily passenger loads with both charging strategies show similar trends. Route-1 still holds the highest CC, and remains the most likely candidate for electrification. Then, Route-2 maintains the second-highest CC scores and ranks second, with Route-3 ranking third across 25%, 50%, 75%, and 100% daily passenger loads. Lastly, Route-4, Route-6, and Route-5 still occupy the bottom three positions.

4.4.4 Scenario 4: All Daily Passenger Loads with Both Charging Strategies

For the scenario across all daily passenger loads and both charging strategies, results were obtained by aggregating all findings from the Scenario 1. This approach allows for viewing the findings at every passenger load factor and regardless of the charging strategy used. The CC scores of each bus route, ranked from highest to lowest, consistently follow this order: Route-1, Route-2, Route-3, Route-4, Route-6, and Route-5, as illustrated in Figure 4.12.



	Route-1	Route-2	Route-3	Route-4	Route-5	Route-6
CCr (25%)	0.7782	0.7360	0.6515	0.5564	0.2702	0.4471
CCr (50%)	0.7782	0.7360	0.6515	0.5564	0.2702	0.4471
CCr (75%)	0.7912	0.7447	0.6668	0.5679	0.2797	0.4354
CCr (100%)	0.7967	0.7362	0.6551	0.5471	0.2502	0.4723
Ranking (25%)	1	2	3	4	6	5
Ranking (50%)	1	2	3	4	6	5
Ranking (75%)	1	2	3	4	6	5
Ranking (100%)	1	2	3	4	6	5

Figure 4.11: The Relationship Between CC_r and Ranking across Different Bus Routes at 25%, 50%, 75%, or 100% Daily Passenger Load with Both Charging Strategies.

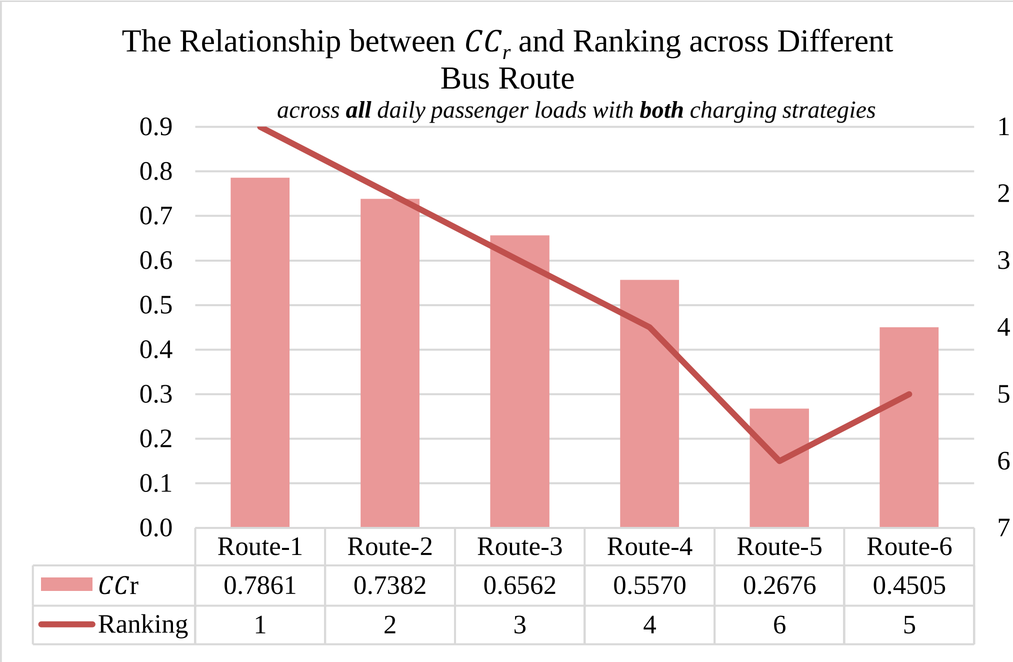


Figure 4.12: The Relationship Between CC_r and Ranking across Different Bus Routes across All Daily Passenger Loads with Both Charging Strategies.

4.4.5 Summary

Based on the four scenarios discussed, the fuzzy TOPSIS analysis provides bus operators with clear guidance on selecting bus routes for BEB operations, whether they have partial or full requirements. Across all scenarios, the rankings remain consistent, with Route-1 being the most favourable for BEB operations, followed by Route-2, Route-3, Route-4, Route-6, and Route-5. This consistency suggests that, regardless of the specific scenario whether considering a certain daily passenger load with a particular strategy of charging (scenario 1), a certain charging strategy regardless of daily passenger load (scenario 2), a certain passenger load regardless of charging strategy (scenario 3), or regardless of both factors (scenario 4) Route-1 (Bandar Sungai Long & Palm Walk (Morning Route)) is identified as the most suitable choice for electrification. If additional routes are to be electrified, the rankings can guide operators in selecting the most suitable candidates for BEB operations.

4.5 Fuzzy TOPSIS Analysis in Determining the Desirable Bus Type for BEB Operations on Each Bus Route

The second part of the fuzzy TOPSIS analysis determines the most suitable bus type for BEB operations for each bus route, as shown in Figure 4.13, this section focuses on selecting the most desirable bus type among the 11 BEBs for each bus route, considering small or big bus size (25 or 44 seats), varying passenger load factor (25%, 50%, 75%, or 100%), and different charging strategies (slow or fast). The discussion then examines the correlation between passenger load factor, bus size and charging strategy. The analysis is divided into five scenarios. Specifically, scenario 5 examines each combination of passenger load factors (25%, 50%, 75%, and 100%) with bus size (small or big) and charging strategy (slow or fast). Scenario 6 looks into the impact of different passenger load factors (25%, 50%, 75%, and 100%) on different bus sizes (small or big) with both charging strategies (slow and fast). Then, scenario 7 compares 25% and 50% passenger load factors across both bus sizes and charging strategies. Later, scenario 8 examines the correlation between 25% and 50% passenger load factors considering both bus sizes and charging strategies and 75% passenger load factors considering small bus sizes with both charging strategies. And, scenario 9 explores the correlation between all passenger loads from different passenger load factors (25%, 50%, 75%, and 100%) with both bus sizes and charging strategies sorted out.

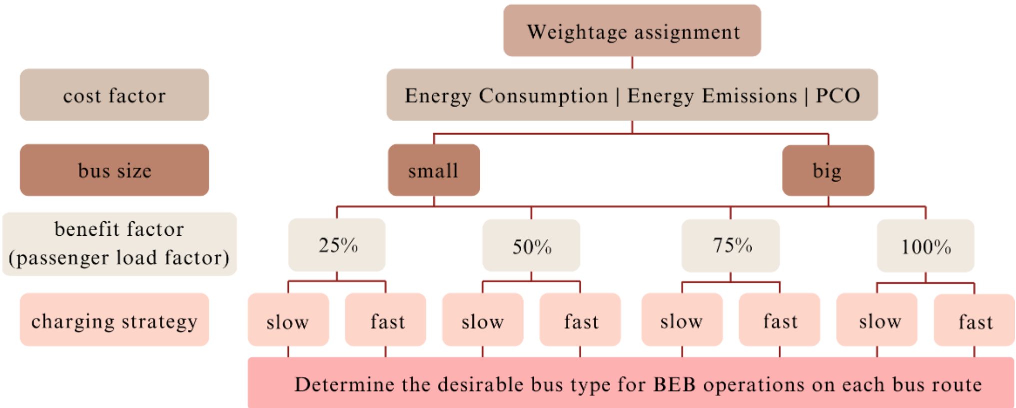


Figure 4.13: Overview of fuzzy TOPSIS Framework in Determining the Desirable Bus Type for BEB Operations on Each Bus Route.

Since not all the 11 BEBs are available for both bus sizes with some are only suitable for small bus size. Therefore, the process of selecting the appropriate bus type for analysis involves four steps as stated below:

Step 1: Select the top three BEBs that are closest in total size to the required passenger load factor.

Step 2: Choose the BEB that ranks first for that particular bus route.

Step 3: Repeat steps 1 and 2 until all the BEBs have been considered.

After evaluating all the BEBs, the initial candidates for each bus size, based on different passenger load factors, are listed in Table 4.15. This assessment has considered scenarios where two buses per trip are used. If the passenger load meets or exceeds twice the capacity of a candidate bus, it is selected for further analysis with two buses per trip.

4.5.1 Scenario 5: 25%, 50%, 75%, or 100% Passenger Load Factors Considering Small or Big Bus Size with Either Slow or Fast Charging Strategies.

As outlined in Table 4.16, Y1 and Y3 dominate all scenarios on Route-1. Initially, Y3 ranks first in scenarios involving 25% and 50% daily passenger loads using the slow charging strategy, as well as in scenarios with a 75% daily passenger load factor using the same strategy. Conversely, Y1 takes the lead in the remaining scenarios, except when replacing large buses with a 100% passenger load factor where Y3 is preferred once again using two buses per trip across all routes.

For Route-2, Y3 leads in all scenarios except when replacing large buses with a 75% passenger load factor and small buses with a 100% passenger load factor, where Y10 takes over. Similarly, Route-4 shows a similar trend, with Y6 replacing large buses at a 75% passenger load factor and small buses at a 100% passenger load factor.

For Route-3, Y8 consistently dominates all scenarios with a 25% passenger load and the fast charging strategy, as well as scenarios with a 50% passenger load and small buses with a 75% passenger load factor. Conversely, Y3 steps in when replacing both bus sizes with a 50% passenger load and small buses with a 75% passenger load under the slow charging strategy. Later, Y2 claimed the top spot for large buses with a 75% passenger load, while Y8 remained the preferred choice for small buses with a 100% passenger load.

For Route-5, Y3 leads in scenarios with a 25% passenger load factor and small buses with a 50% passenger load factor. Then Y4 emerges as the top choice for BEB operations. As the passenger load factor increases to 75% for large buses, Y2 initially takes the lead, but Y4 gradually overtakes, securing the top spot for replacing small buses with a 100% passenger load factor. Meanwhile, Y3 continues to be favoured for replacing large buses with a 100% passenger load.

Finally, Y2 dominates most scenarios on Route-6, except when replacing large buses with a 100% passenger load. The full details of CC and ranking of each bus route is listed in Appendix H.

4.5.2 Scenario 6: 25%, 50%, 75%, or 100% Passenger Load Factors Considering Small or Big Bus Size with Both Charging Strategies

As presented in Table 4.14, the findings indicate a consistent preference for BEB operations at a 25% passenger load factor across all bus routes. The recommended BEBs are Y3 for Route-1, Routes-2, Route-4 and Route-5, Y8 for Route-3 and Y2 for Route-6.

When the passenger load factor increases to 50%, the analysis shows a similar trend for both small and big buses. Y3 emerges as the preferred choice from Route-1 to Route-4, while Y2 is most likely to be selected for Route-6. For Route-1, Y1 is recommended for replacing small buses, and Y3 for replacing big buses. For Route-5, Y3 is suggested for small buses, with Y4 being the favoured option for big buses.

At a 75% passenger load factor, there is a clear preferences for both small and big buses across all routes. For small buses, Y3 consistently emerges as the top choice across Routes-1 to Route-2 and Route-4, while Y8 is preferred for Route-3, Y4 for Route-5 and Y2 for Route-6 . When it comes to big buses, the preferences shift slightly. Y1 is the recommended option for

Route-1, with Y10, Y2 and Y6 being the top choice for Routes-2 to Route-4, respectively. For Route-5 and Route-6, Y2 remains the top choice for replacing big buses.

Besides, the results highlight that Y1 is the leading choice on Route-1, while Route-2 sees Y10 as the most suitable option. For Route-3, Y8 stands out as the preferred bus, with Y6 taking the lead on Route-4. Meanwhile, Y4 and Y2 are recommended for Route-5 and Route-6, respectively at the 100% passenger load factor. For big buses, Y3 is consistently identified as the best option across all routes. However, due to the full passenger load, the analysis suggests employing two buses per trip to ensure efficient service on these routes.

Table 4.14: Bus Type That Ranks First Under Scenarios of 25%, 50%, 75%, or 100% Passenger Load Factors Considering Small or Big Bus Size with Both Charging Strategies.

Passenger load factor	Bus Size	Bus Route					
		1	2	3	4	5	6
25%	Small	Y3	Y3	Y8	Y3	Y3	Y2
	Big	Y3	Y3	Y8	Y3	Y3	Y2
50%	Small	Y3	Y3	Y3	Y3	Y3	Y2
	Big	Y3	Y3	Y3	Y3	Y4	Y2
75%	Small	Y3	Y3	Y8	Y3	Y4	Y2
	Big	Y1	Y10	Y2	Y6	Y2	Y2
100%	Small	Y1	Y10	Y8	Y6	Y4	Y2
	Big	*Y3					
Remarks: * indicates two buses per trip							

Table 4.15: Candidate BEBs for Analysis.

<table>
<tr><th rowspan="2">Passenger load factor</th><th rowspan="2">Bus Size</th><th colspan="6">Bus Route</th></tr>
<tr><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th><th>6</th></tr>
<tr><td rowspan="2">25%</td><td>Small</td><td rowspan="3">(1) Y1
(2) Y3
(3) Y5
(4) Y7
(5) Y8
(6) Y9
(7) Y11</td><td rowspan="3">(1) Y3
(2) Y8
(3) Y10
(4) Y11</td><td rowspan="3">(1) Y3
(2) Y8
(3) Y11</td><td rowspan="3">(1) Y3
(2) Y6
(3) Y8
(4) Y11</td><td rowspan="3">(1) Y3
(2) Y4
(3) Y8
(4) Y11</td><td rowspan="3">(1) Y2
(2) Y3
(3) Y8
(4) Y11</td></tr>
<tr><td>Big</td></tr>
<tr><td rowspan="2">50%</td><td>Small</td></tr>
<tr><td>Big</td><td rowspan="2">(1) Y1
(2) Y3
(3) Y5
(4) Y7
(5) Y8
(6) Y9</td><td rowspan="2">(1) Y3
(2) Y7
(3) Y8
(4) Y10</td><td rowspan="2">(1) Y3
(2) Y7
(3) Y8</td><td rowspan="2">(1) Y3
(2) Y6
(3) Y7
(4) Y8</td><td rowspan="2">(1) Y3
(2) Y4
(3) Y7
(4) Y8</td><td rowspan="2">(1) Y2
(2) Y3
(3) Y7
(4) Y8</td></tr>
<tr><td rowspan="2">75%</td><td>Small</td></tr>
<tr><td>Big</td><td>(1) Y1
(2) Y2
(3) Y4
(4) Y5
(5) Y9
(6) *Y11</td><td>(1) Y2
(2) Y4
(3) Y10
(4) *Y11</td><td>(1) Y2
(2) Y4
(3) *Y11</td><td>(1) Y2
(2) Y4
(3) Y6
(4) *Y11</td><td colspan="2">(1) Y2
(2) Y4
(3) *Y11</td></tr>
<tr><td rowspan="2">100%</td><td>Small</td><td>(1) Y1
(2) Y4
(3) Y5
(4) Y7
(5) Y8
(6) Y9</td><td>(1) Y4
(2) Y7
(3) Y8
(4) Y10</td><td>(1) Y4
(2) Y7
(3) Y8</td><td>(1) Y4
(2) Y6
(3) Y7
(4) Y8</td><td>(1) Y4
(2) Y7
(3) Y8</td><td>(1) Y2
(2) Y4
(3) Y7
(4) Y8</td></tr>
<tr><td>Big</td><td colspan="6">(1) Y1
(2) Y6
(3) *Y3</td></tr>
<tr><td colspan="8">Remarks: * indicates two buses per trip</td></tr>
</table>

Table 4.16: Bus Type That Ranks First Under Scenarios of 25%, 50%, 75%, or 100% Passenger Load Factors Considering Small or Big Bus Size with Either Slow or Fast Charging Strategies.

Passenger load factor	Bus Size	Charging Strategy	Bus Route					
			1	2	3	4	5	6
25%	Small	Slow	Y3	Y3	Y8	Y3	Y3	Y2
		Fast	Y1	Y3	Y8	Y3	Y3	Y2
	Big	Slow	Y3	Y3	Y8	Y3	Y3	Y2
		Fast	Y1	Y3	Y8	Y3	Y3	Y2
50%	Small	Slow	Y3	Y3	Y3	Y3	Y3	Y2
		Fast	Y1	Y3	Y8	Y3	Y3	Y2
	Big	Slow	Y3	Y3	Y3	Y3	Y4	Y2
		Fast	Y1	Y3	Y8	Y3	Y4	Y2
75%	Small	Slow	Y3	Y3	Y3	Y3	Y4	Y2
		Fast	Y1	Y3	Y8	Y3	Y4	Y2
	Big	Slow	Y1	Y10	Y2	Y6	Y2	Y2
		Fast	Y1	Y10	Y2	Y6	Y2	Y2
100%	Small	Slow	Y1	Y10	Y8	Y6	Y4	Y2
		Fast	Y1	Y10	Y8	Y6	Y4	Y2
	Big	Slow	*Y3	*Y3	*Y3	*Y3	*Y3	*Y3
		Fast	*Y3	*Y3	*Y3	*Y3	*Y3	*Y3
Remarks: (1) * indicates two buses per trip								

4.5.3 Scenario 7: 25% and 50% Passenger Load Factors Considering Both Bus Sizes with Both Charging Strategies

All bus candidates are well suited to replace both small and big buses at 25% load factors as their capacity meets the decreased demand Similarly, at a 50% passenger load factor, all candidates are appropriate for both bus sizes, after eliminating Y11 since its maximum capacity is 17 passenger seats where is not able to replace big buses with 50 passenger load factors.

As presented in Table 4.17, the analysis identifies that at a 25% passenger load factor, Y3 as the preferrable choice for Route-1, Route-2, Route-4 and Route-5. While Y8 as the preferred option for Routee-3 and with Y2 for Route-6. When the passenger load increases to 50%, Y3 emerges as the favoured bus type for Routes-1 to Route-4. Y4 is recommended for Route-5, while Y2 is still the preferred option for Route-6. These recommendations are outlined based on the alignment of each bus type's capacity with the corresponding passenger load requirements, ensuring effective and efficient operations across the routes.

Table 4.17: Bus Type That Ranks First Under Scenarios of 25% and 50% Passenger Load Factors Considering Both Bus Sizes with Both Charging Strategies.

Passenger load factor	Bus Size	Bus Route					
		1	2	3	4	5	6
25%	Both	Y3	Y3	Y8	Y3	Y3	Y2
50%	Both	Y3	Y3	Y3	Y3	Y4	Y2

4.5.4 Scenario 8: Converting from Passenger Load Factors to Passenger Load

Since the recommended bus candidates remain similar across all routes for 25% and 50% passenger load factors, regardless of bus size and charging strategies, as well as across all routes for small buses at a 75% passenger load factor, the fuzzy TOPSIS analysis continues to focus on evaluating the most suitable bus types for varying passenger load factors. Specifically, it assesses bus types for 25% and 50% passenger load factors, taking into account both bus sizes and charging strategies, while also evaluating the performance of small buses at a 75% passenger load factor.

As presented in Table 4.18, for a passenger load of less than 23, the fuzzy TOPSIS analysis recommends specific bus types for each route to ensure optimal performance. For Route-1, Route-2 and Route-4, Y3 is identified as the most suitable choice. For Rotue-3, Y8 is preferred, while Route-5 sees Y4 as the ideal solution for handling the load effectively. And, Y2 is identified as the most appropriate choice for Route-6. These recommendations are outlined to match the lower passenger load efficiently across all routes.

Table 4.18: Converting from Passenger Load Factors To Passenger Load.

Passenger load factor	Bus Size	Bus Route					
		1	2	3	4	5	6
25%	Both	Y3	Y3	Y8	Y3	Y3	Y2
50%	Both	Y3	Y3	Y3	Y3	Y4	Y2
75%	Small	Y3	Y3	Y8	Y3	Y4	Y2

Passenger load	Bus Route					
	1	2	3	4	5	6
≤22	Y3	Y3	Y8	Y3	Y4	Y2

4.5.5 Scenario 9: 25%, 50%, 75% and 100% Passenger Load Factors Considering Both Bus Sizes with Both Charging Strategies

This section converts all passenger load factors into actual passenger numbers to present an alternative perspective in suggesting the most suitable bus types. Table 4.19 provides a detailed breakdown of the most desirable bus types for various passenger loads across different routes. For passenger loads of 22 or fewer, the recommended bus types are Y3 for Route-1 and Route-2 while Y8 for Route-3, Y3 for Route-4, Y4 for Route-5, and Y2 for Route-6. As the passenger load increases to 25, Y1 becomes the preferred option for Route-1, while Y10 is recommended for Route-2, Y8 for Route-3, with Y6, Y4, and Y2 remaining suitable for Route-4 through Route-6. At a passenger load of 33, Y1 remains the top choice for Route-1, Y10 for Route-2, and Y2 for Route-3 and Route-5 to Route-6, with Y6 being recommended for Route-4. For the maximum capacity of 44 passengers, Y3 is identified as the most effective option for all routes, with the recommendation that two buses per trip are necessary to accommodate the higher capacity efficiently.

Table 4.19: Scenarios of Passenger Load According to 25%, 50%, 75% and 100% Passenger Load Factors Considering Both Bus Sizes with Both Charging Strategies.

<table>
<tr><th rowspan="2">Passenger load</th><th colspan="6">Bus Route</th></tr>
<tr><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th><th>6</th></tr>
<tr><td>≤22</td><td colspan="2">Y3</td><td rowspan="2">Y8</td><td>Y3</td><td rowspan="2">Y4</td><td rowspan="3">Y2</td></tr>
<tr><td>≤25</td><td rowspan="2">Y1</td><td rowspan="2">Y10</td><td rowspan="2">Y6</td></tr>
<tr><td>≤33</td><td>Y2</td><td>Y2</td></tr>
<tr><td>≤44</td><td colspan="6">*Y3</td></tr>
<tr><td colspan="7">Remarks: * indicates two buses per trip</td></tr>
</table>

4.5.6 Summary

Based on the discussions above, it could be seen that fuzzy TOPSIS analysis provides bus operators with clear guidance on selecting the most suitable bus type for BEB operations on each route. Generally, each BEB has distinct specifications, making not all BEBs appropriate for every route. Overall, the framework outlines the most desirable bus types based on various combinations of passenger load factors, bus sizes, and charging strategies in which the bus operators may disregard the charging strategy and focus solely on identifying the most desirable bus type for different passenger load factors and bus sizes. Finally, the framework sorts of passenger load across all passenger load factors, bus sizes, and charging strategies, providing bus operators with a clear approach to determining the most favourable bus type for their needs.

4.6 Analysis of fuzzy TOPSIS in Determining the Desirable Bus Route for BEB Operations

Based on the findings from the initial phase of the fuzzy TOPSIS analysis discussed in Chapter 4.4, this section delves into the criteria (supply and demand aspect) influencing the ranking of bus routes. The first part explores how the relationship among supply aspects shapes the rankings of each bus route. The second part investigates how the weightage of criteria impacts the final ranking of the bus routes.

4.6.1 The Relationship among Supply Aspects across Different Bus Routes

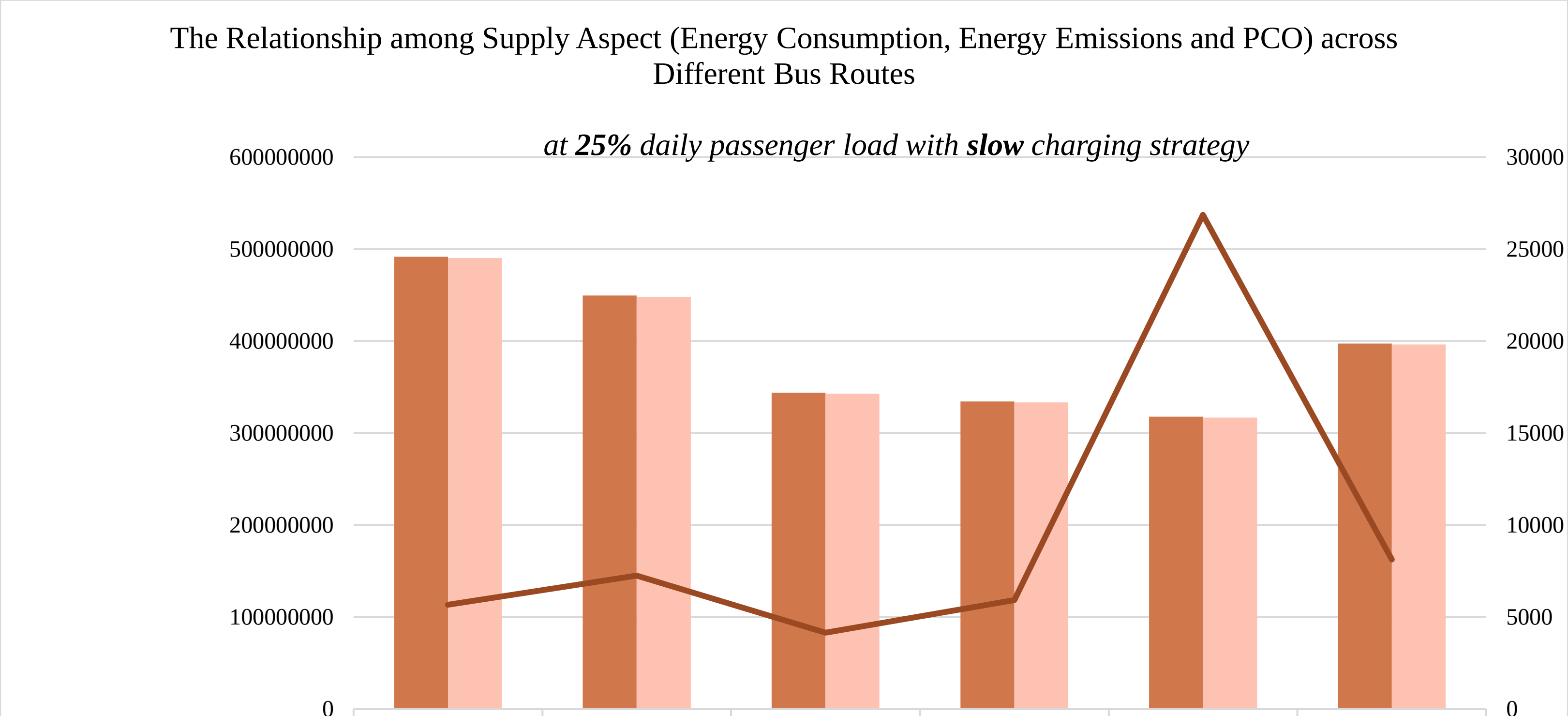
This section explores how the supply aspects (energy consumption, emissions, and PCO) affect the rankings of each bus route with scenario 10: individual cases at 25%, 50%, 75%, and 100% daily passenger loads with either slow or fast charging strategies, scenario 11: across all daily passenger loads with either slow or fast charging strategies, scenario 12: 25%, 50%, 75%, or 100% daily passenger load with both charging strategies and scenario 13: all daily passenger loads with both charging strategies.

4.6.1.1 Scenario 10: 25%, 50%, 75%, or 100% Daily Passenger Loads with Either Slow or Fast Charging Strategies

All the figures presented in this section show the relationship among supply aspects (energy consumption, energy emissions and PCO) across different criteria as listed in Table 4.20 below.

Table 4.20: Scenarios of Different Daily Passenger Loads with Different Charging Strategies and Corresponding Figures Listed.

Scenario	Figure
25% Daily Passenger Load with Slow Charging Strategy	Figure 4.14
25% Daily Passenger Load with Fast Charging Strategy	Figure 4.15
50% Daily Passenger Load with Slow charging strategy	Figure 4.16
50% Daily Passenger Load with Fast Charging Strategy	Figure 4.17
75% Daily Passenger Load with Slow Charging Strategy	Figure 4.18
75% Daily Passenger Load with Fast Charging Strategy	Figure 4.19
100% Daily Passenger Load with Slow Charging Strategy	Figure 4.20
100% Daily Passenger Load with Fast Charging Strategy	Figure 4.21



	Route-1	Route-2	Route-3	Route-4	Route-5	Route-6
Energy Consumption (kW)	491780369.9563	449673271.0284	343914370.0591	334286991.6059	317750589.8284	397553960.7236
Energy Emissions (kW)	490305028.8465	448324251.2154	342882626.9490	333284130.6311	316797338.0590	396361298.8414
PCO (RM)	5670.56	7260.81	4149.15	5926.04	26866.00	8132.00

Figure 4.14: The Relationship among Supply Aspects (Energy Consumption, Energy Emissions and PCO) across Different Bus Routes at 25% Daily Passenger Load with Slow Charging Strategy.

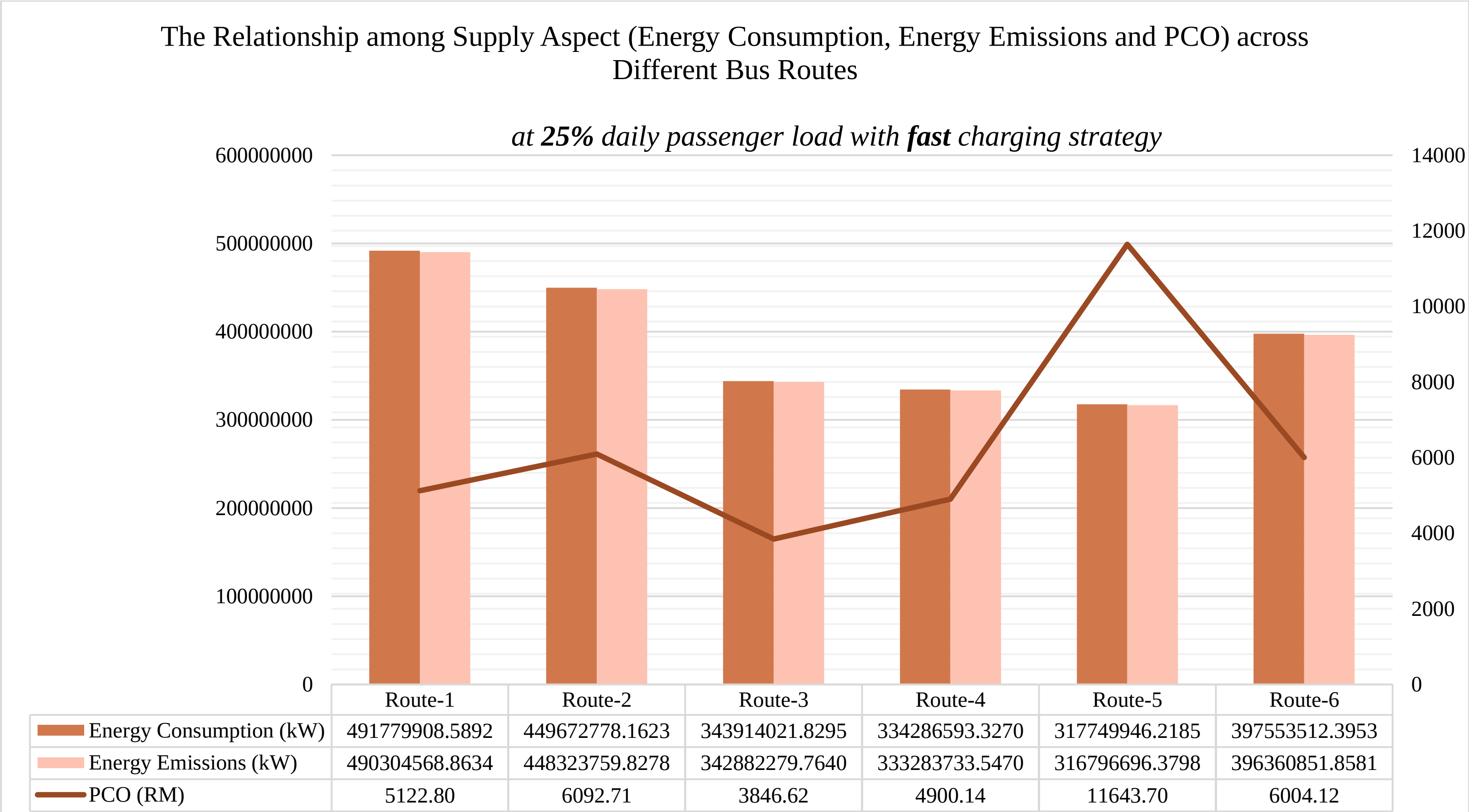


Figure 4.15: The Relationship among Supply Aspects (Energy Consumption, Energy Emissions and PCO) across Different Bus Routes at 25% Daily Passenger Load with Fast Charging Strategy.

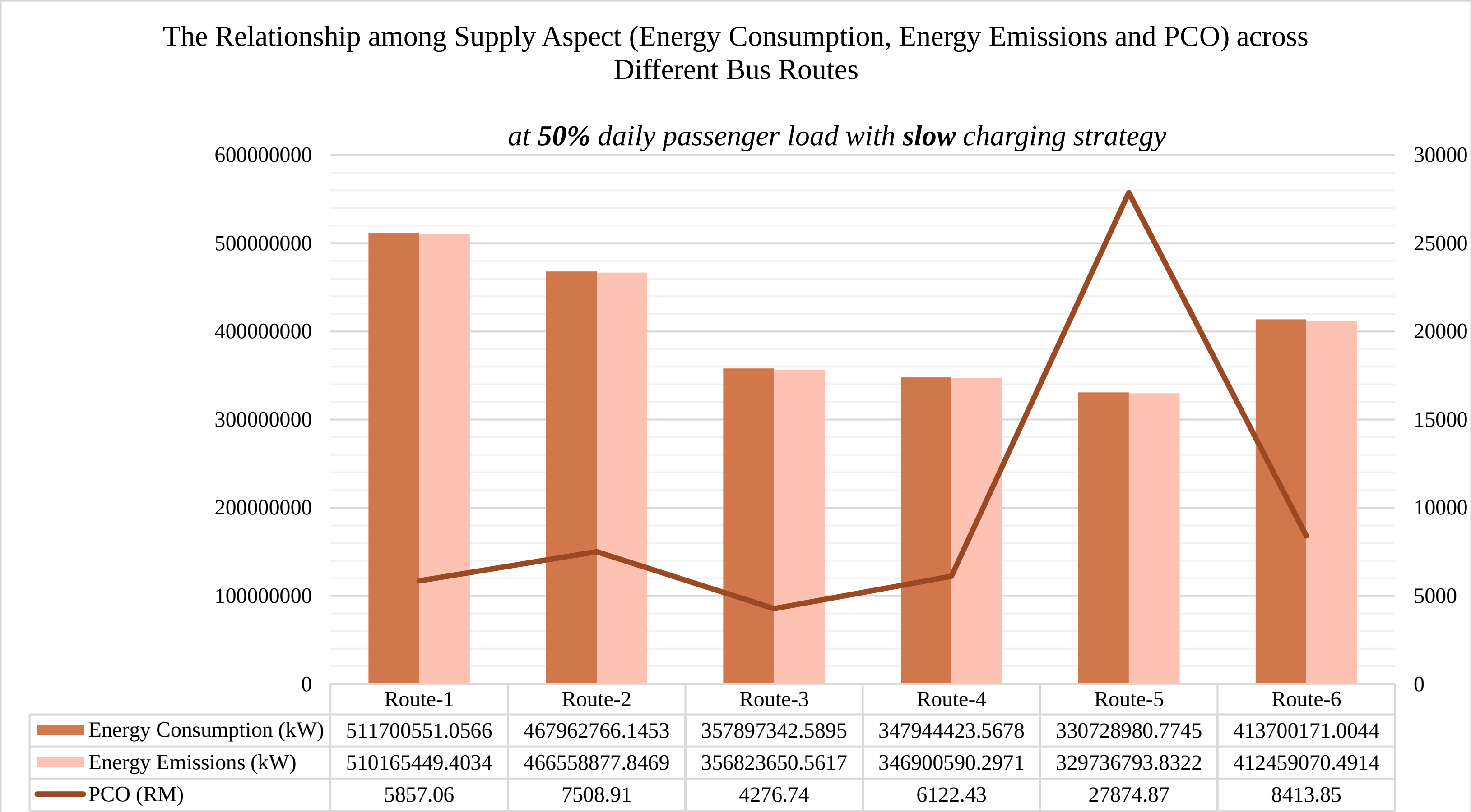
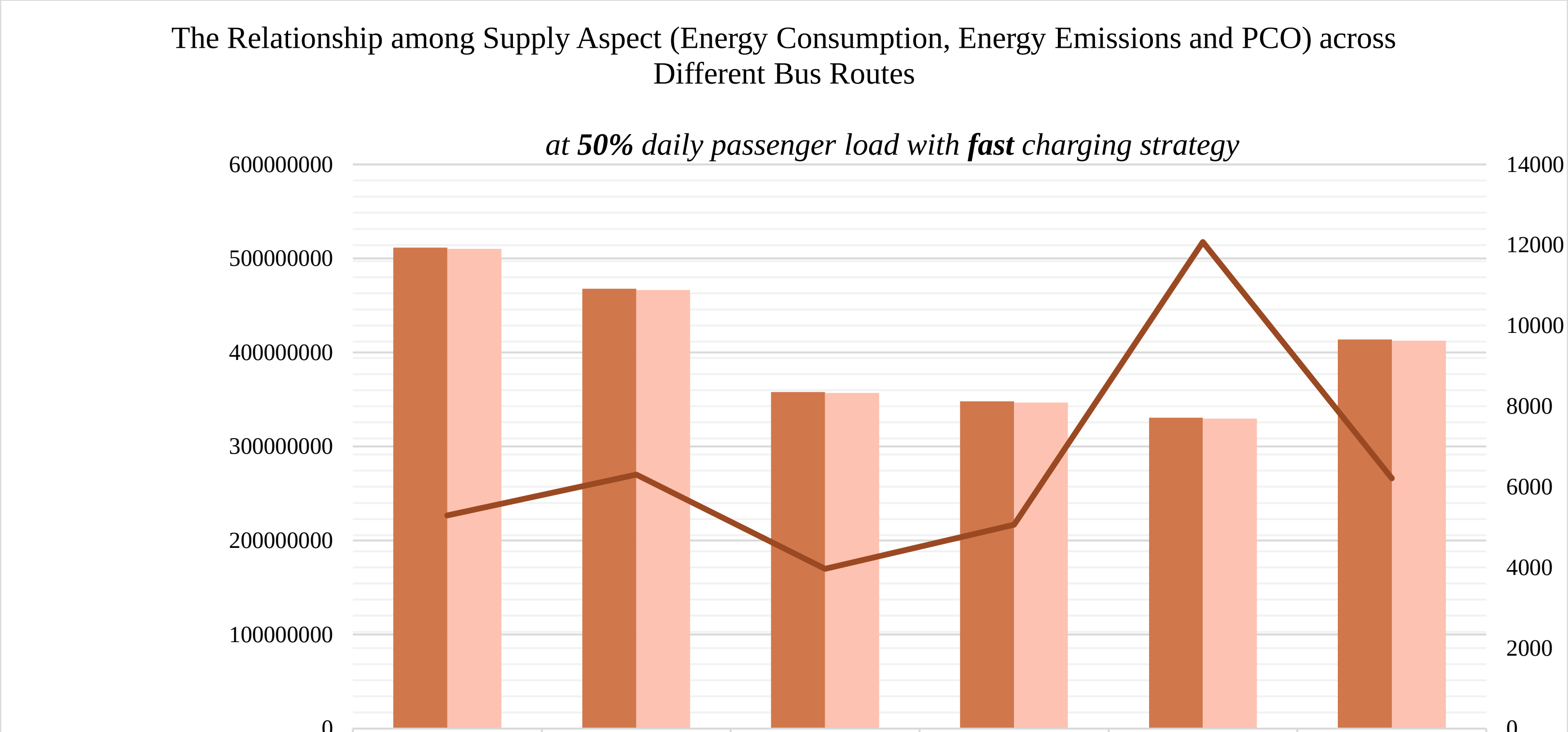
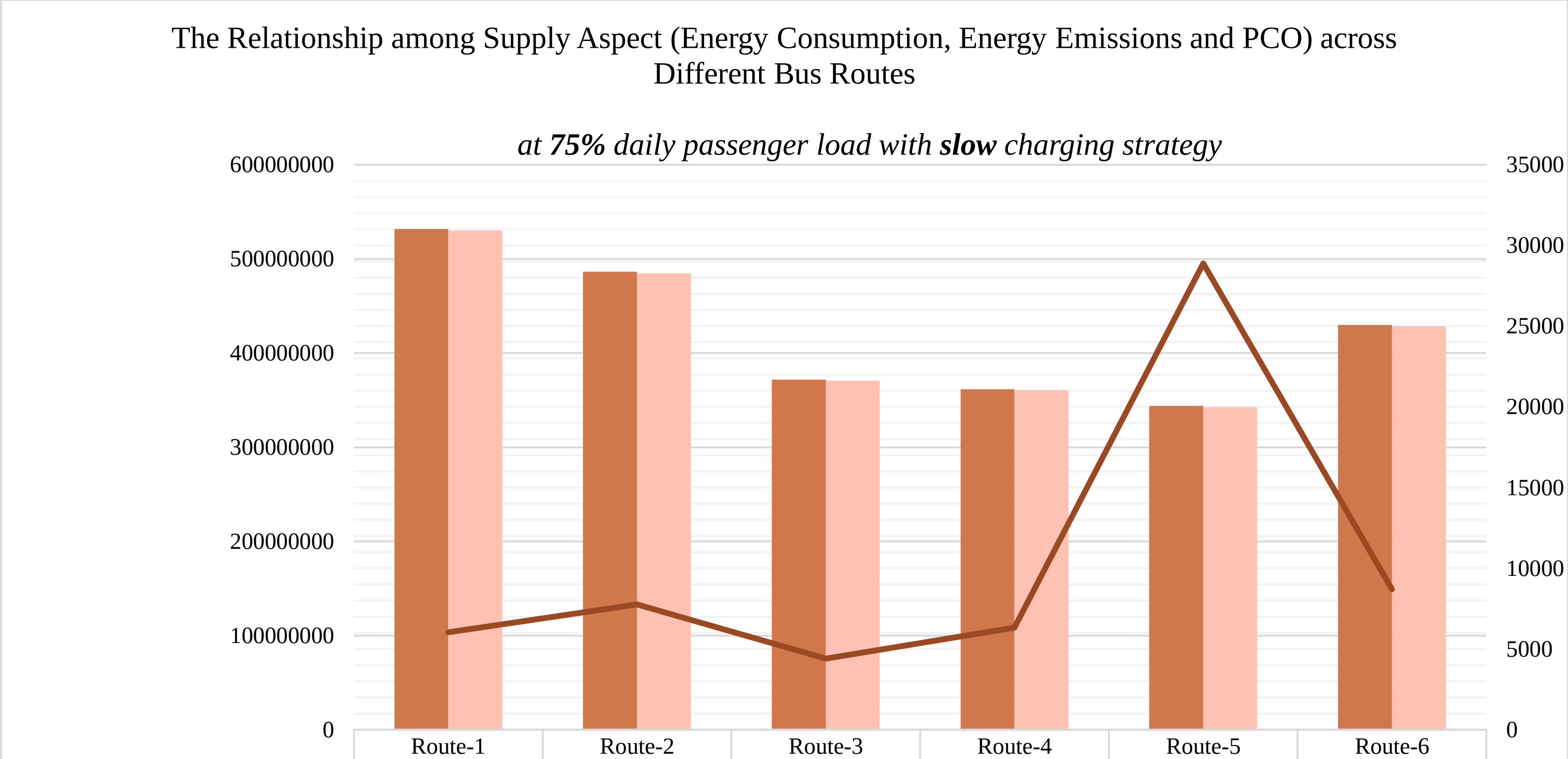


Figure 4.16: The Relationship among Supply Aspects (Energy Consumption, Energy Emissions and PCO) across Different Bus Routes at 50% Daily Passenger Load with Slow Charging Strategy.



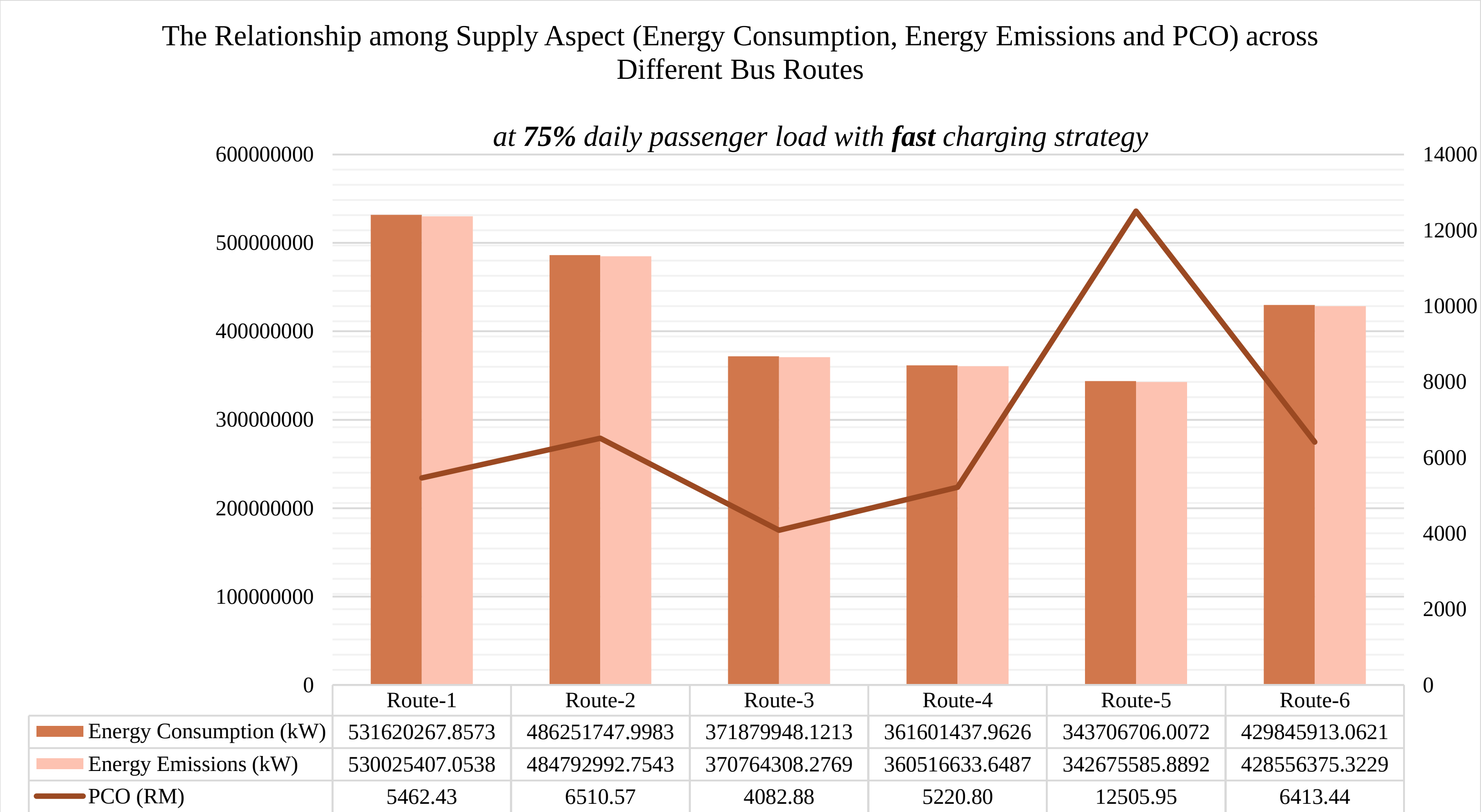
	Route-1	Route-2	Route-3	Route-4	Route-5	Route-6
Energy Consumption (kW)	511700088.2233	467962254.6289	357896976.5231	347944007.1707	330728317.6665	413699704.2764
Energy Emissions (kW)	510164987.9586	466558367.8651	356823285.5936	346900175.1492	329736132.7135	412458605.1636
PCO (RM)	5292.62	6301.64	3964.75	5060.47	12074.82	6208.78

Figure 4.17: The Relationship among Supply Aspects (Energy Consumption, Energy Emissions and PCO) across Different Bus Routes at 50% Daily Passenger Load with Fast Charging Strategy.



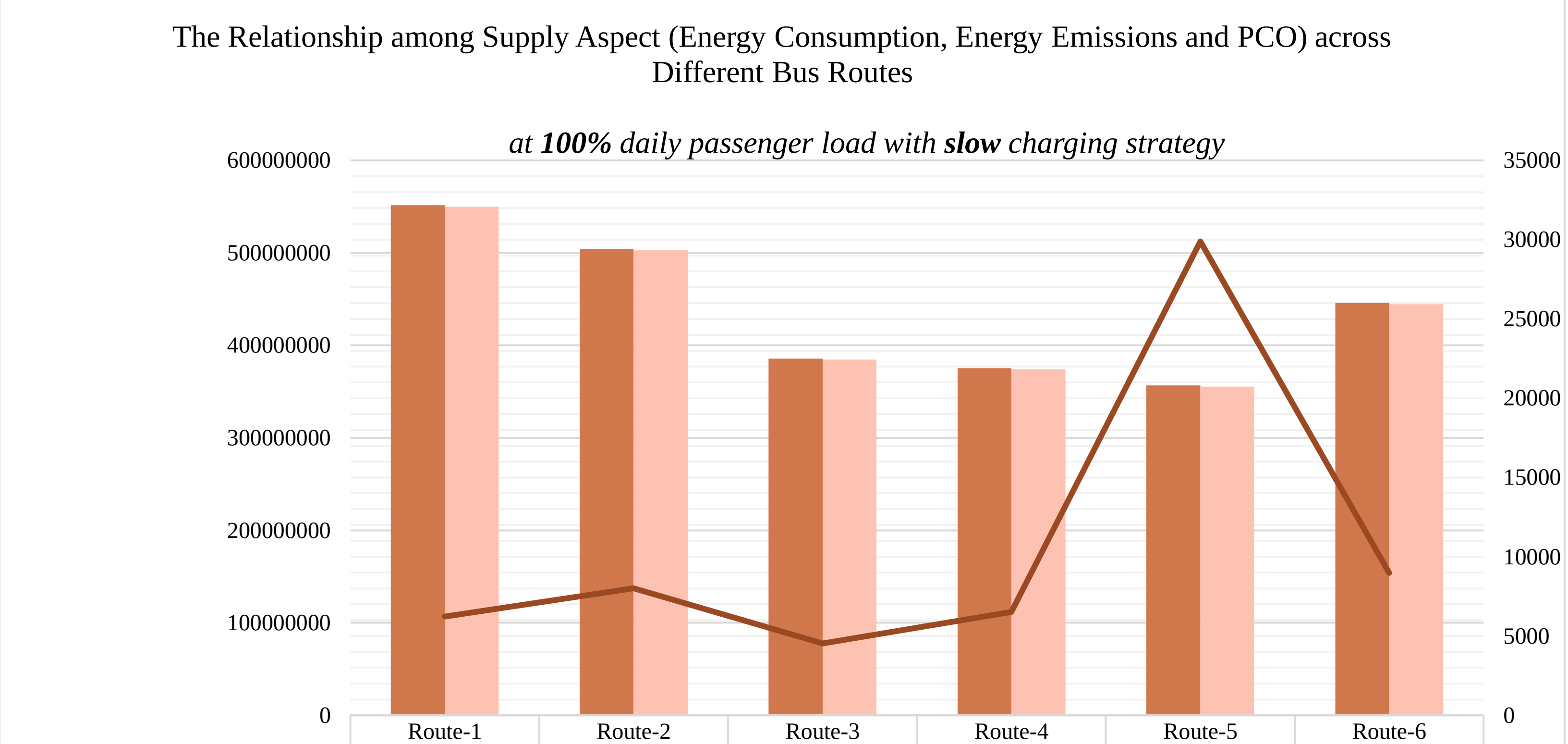
	Route-1	Route-2	Route-3	Route-4	Route-5	Route-6
Energy Consumption (kW)	531620732.1568	486252261.2531	371880315.1125	361601855.5662	343707371.7015	429846381.2780
Energy Emissions (kW)	530025869.9603	484793504.4694	370764674.1672	360517049.9995	342676249.5864	428556842.1341
PCO (RM)	6043.56	7757.01	4404.34	6318.81	28883.75	8695.71

Figure 4.18: The Relationship among Supply Aspects (Energy Consumption, Energy Emissions and PCO) across Different Bus Routes at 75% Daily Passenger Load with Slow Charging Strategy.



	Route-1	Route-2	Route-3	Route-4	Route-5	Route-6
Energy Consumption (kW)	531620267.8573	486251747.9983	371879948.1213	361601437.9626	343706706.0072	429845913.0621
Energy Emissions (kW)	530025407.0538	484792992.7543	370764308.2769	360516633.6487	342675585.8892	428556375.3229
PCO (RM)	5462.43	6510.57	4082.88	5220.80	12505.95	6413.44

Figure 4.19: The Relationship among Supply Aspects (Energy Consumption, Energy Emissions and PCO) across Different Bus Routes at 75% Daily Passenger Load with Fast Charging Strategy.



	Route-1	Route-2	Route-3	Route-4	Route-5	Route-6
Energy Consumption (kW)	551540913.2752	504541756.3791	385863287.6574	375259287.5717	356685762.6348	445992591.5661
Energy Emissions (kW)	549886290.5354	503028131.1100	384705697.7945	374133509.7090	355615705.3469	444654613.7914
PCO (RM)	6230.05	8005.11	4531.94	6515.20	29892.62	8977.57

Figure 4.20: The Relationship among Supply Aspects (Energy Consumption, Energy Emissions and PCO) across Different Bus Routes at 100% Daily Passenger Load with Slow Charging Strategy.

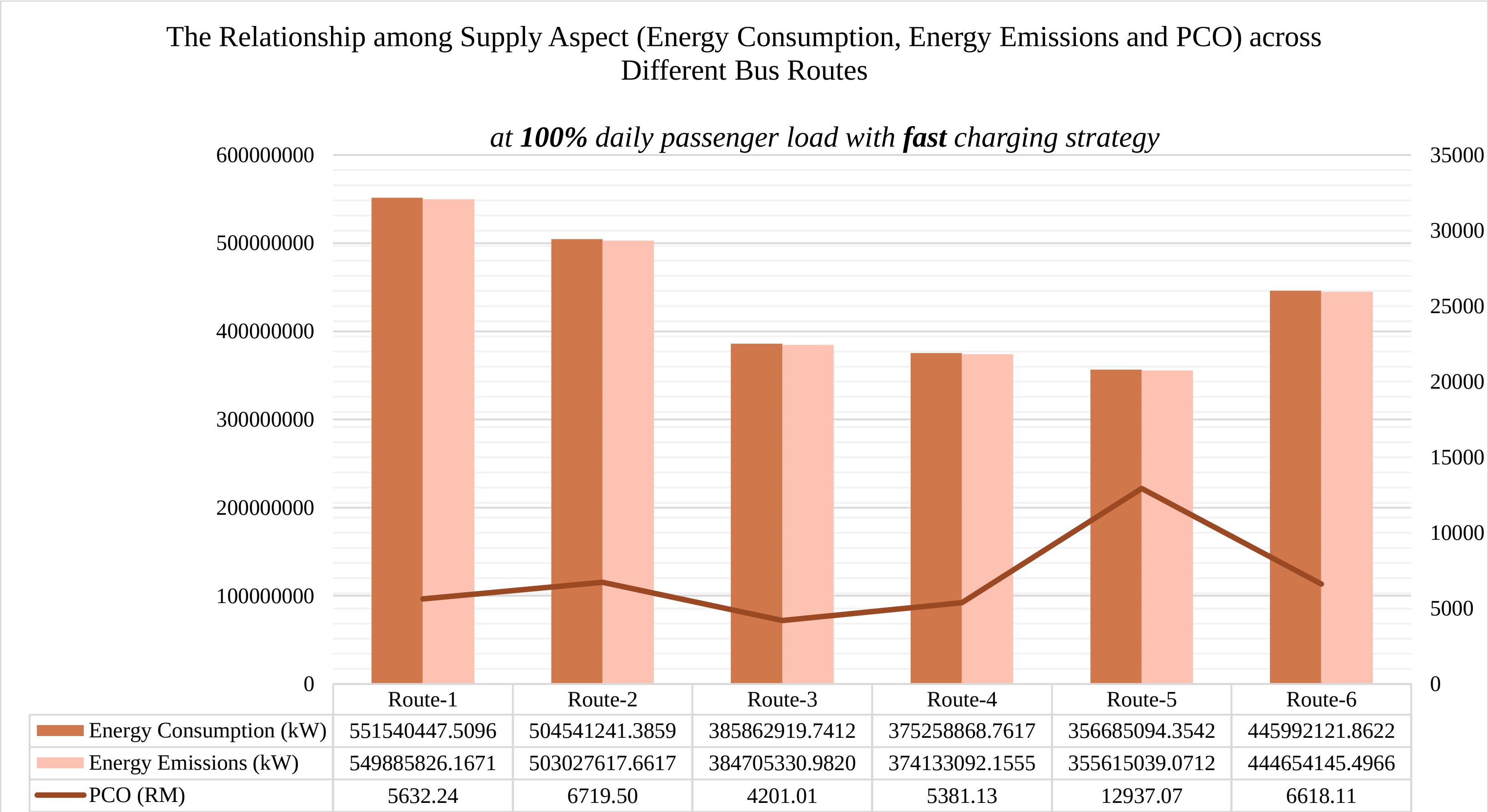


Figure 4.21: The Relationship among Supply Aspects (Energy Consumption, Energy Emissions and PCO) across Different Bus Routes at 100% Daily Passenger Load with Fast Charging Strategy.

Across all scenarios, as displayed from Figure 4.14 to Figure 4.21, Route-5 shows the lowest energy consumption and emissions, followed closely by Route-4 and Route-3, with Route-4 having a slightly lower energy score than Route-3. Route-6 ranks fourth, while Routes 2 and 1 occupy the bottom positions, with Route-2 slightly outperforming Route-1 in terms of energy score. From the perspective of PCO, Route-3 possesses the lowest operating costs among all six bus routes. Following closely is Route-1, and Route-4 with slightly higher operating costs ranks third. Next in the ranking is Route-2 in fourth place and Route-6 in fifth. Route-5, with PCO three times higher than the lowest, firmly holds the last position, with no other bus routes coming close.

When considering only the energy aspect, Route-5 appears to be the most desirable bus route for BEB operations due to its lowest energy score. However, Route-3 also emerges as a strong contender with the lowest PCO. Therefore, the analysis extends to the overall supply aspect (energy consumption, emissions, and PCO) to determine performance of each bus route and check out whether Route-3 or Route-5 is the most desirable bus route for BEB operations.

Across all scenarios, Route-3 stands out with the lowest combined total of energy consumption, emissions, and PCO, with Route-4 closely following. Route-1 secures the third position, with Route-2 just behind. Routes 6 and 5 occupy the bottom positions, with Route-5 falling significantly behind in last place. Notably, Route-5 is no longer the top candidate for BEB operations but rather the least favourable, due to its exceptionally high PCO, which cannot be matched by any other bus routes. Consequently, Route-3 surpasses Route-5 to become the first choice for BEB operations.

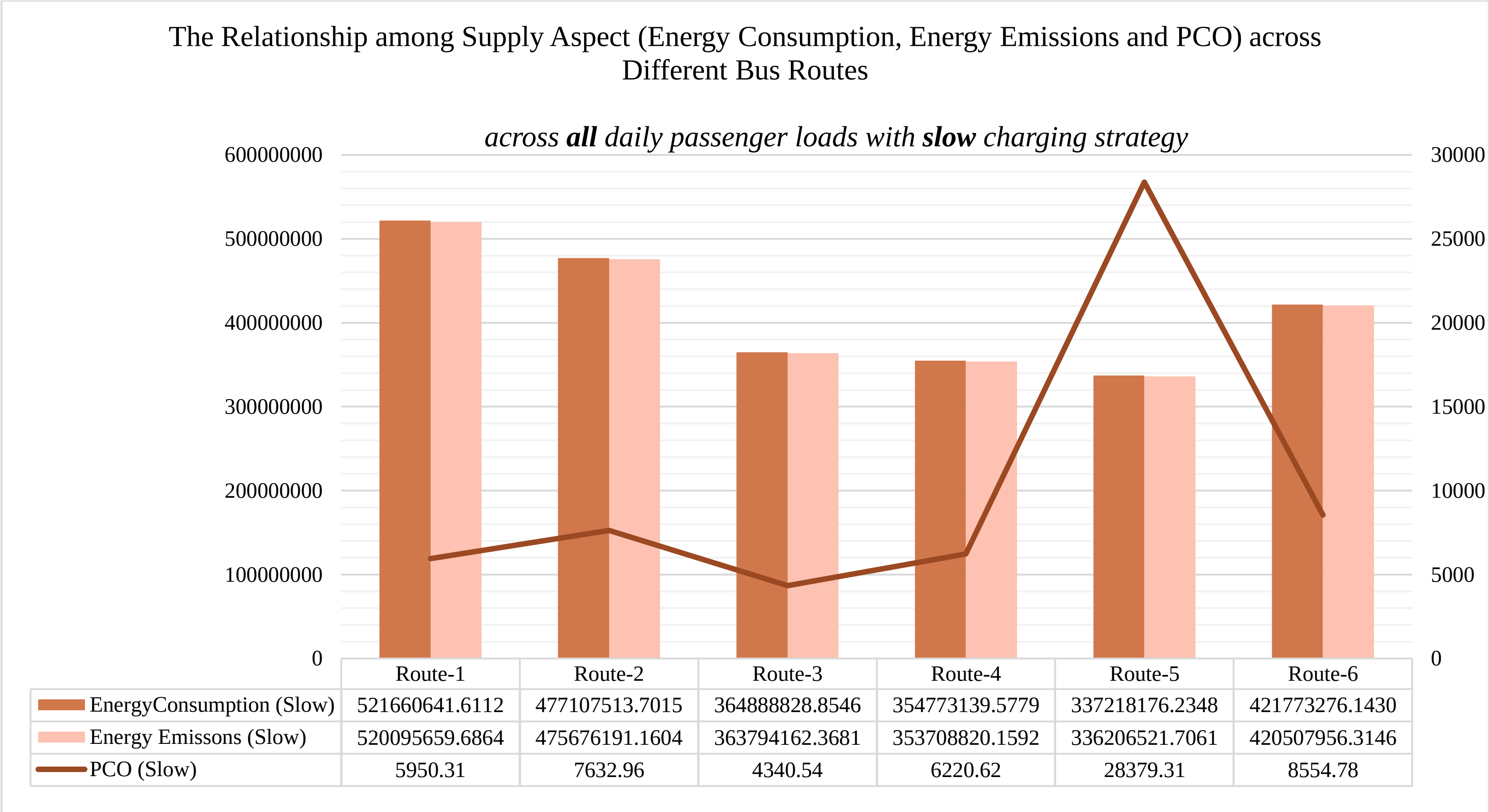
4.6.1.2 Scenario 11: Across All Daily Passenger Loads with Either Slow or Fast Charging Strategies

As illustrated in Figure 4.22 and Figure 4.23, the relationship among supply aspects across different bus routes is analysed, considering both slow and fast charging strategies. Regardless of the charging types, the results consistently show that Route-5 has the lowest energy consumption and emissions but Route-5 stands out on the opposite end in PCO, with significantly higher operating costs compared to the other routes.

When combining the results across all three supply aspects, Route-3, with its lowest PCO, emerges as the most efficient supply aspect. Despite Route-5's lowest energy consumption and emissions, it’s extremely high PCO results in it having the highest total supply aspect, making it the highest supply aspect. Considering only the supply aspects, it can be concluded that regardless of daily passenger load with the use of either slow or fast charging techniques, Route-3 has the potential to become the most preferred bus route for BEB operations. And it is followed by Route-4, Route-1, Route-2, and Route-6, with Route-5 being the least favourable.

4.6.1.3 Scenario 12: 25%, 50%, 75%, or 100% Daily Passenger Load With Both Charging Strategies

As shown from Figure 4.24 to Figure 4.27, regardless of daily passenger load with both charging methods, Route-5 consistently exhibits the lowest energy related metrics, whereas Route-3 stands out for having the lowest PCO. When these individual supply aspects are combined, Route-3 emerges as having the lowest overall supply aspect. In contrast, Route-5 ranks highest in total supply aspect due to its significantly high PCO. Consequently, when evaluating solely on the basis of supply aspects at different daily passenger load levels and using both charging type, Route-3 is recommended as the most suitable bus route for BEB operations, followed sequentially by Route-4, Route-1, Route-2, Route-6, and Route-5.



	Route-1	Route-2	Route-3	Route-4	Route-5	Route-6
EnergyConsumption (Slow)	521660641.6112	477107513.7015	364888828.8546	354773139.5779	337218176.2348	421773276.1430
Energy Emissons (Slow)	520095659.6864	475676191.1604	363794162.3681	353708820.1592	336206521.7061	420507956.3146
PCO (Slow)	5950.31	7632.96	4340.54	6220.62	28379.31	8554.78

Figure 4.22: The Relationship among Supply Aspects (Energy Consumption, Energy Emissions and PCO) across Different Bus Routes and All Daily Passenger Loads with Slow Charging Strategy.

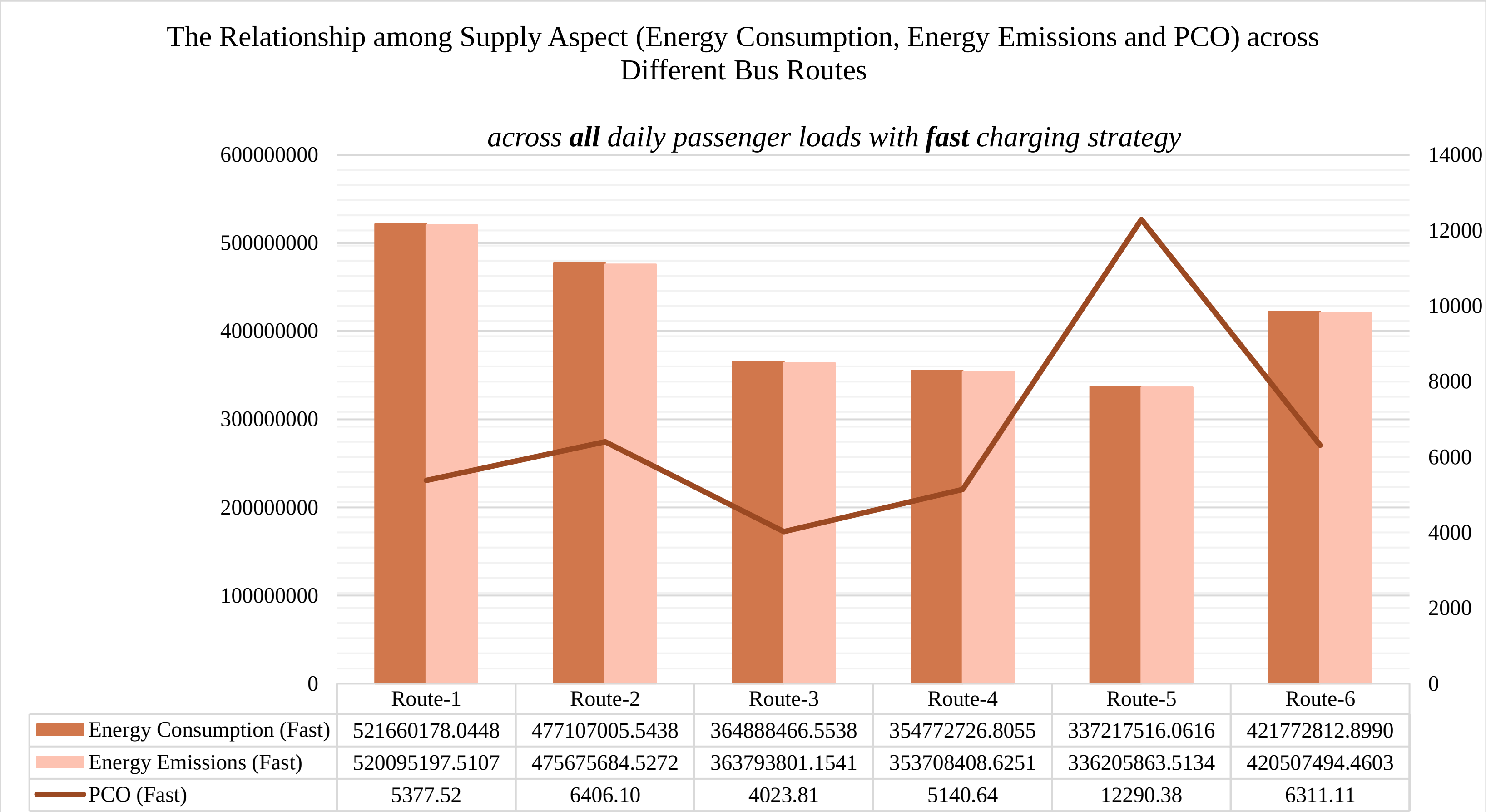


Figure 4.23: The Relationship among Supply Aspects (Energy Consumption, Energy Emissions and PCO) across Different Bus Routes and All Daily Passenger Loads with Fast Charging Strategy.

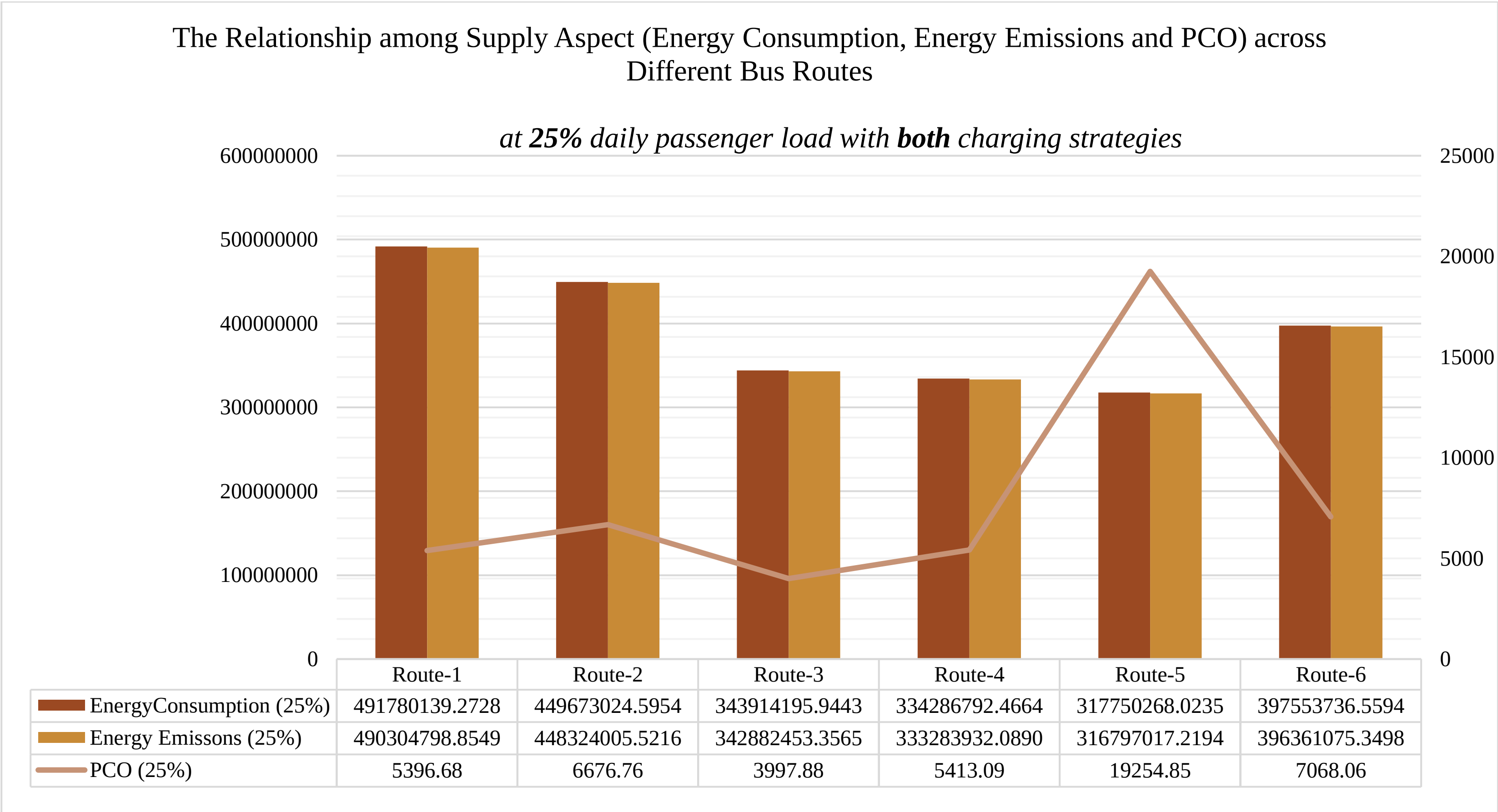
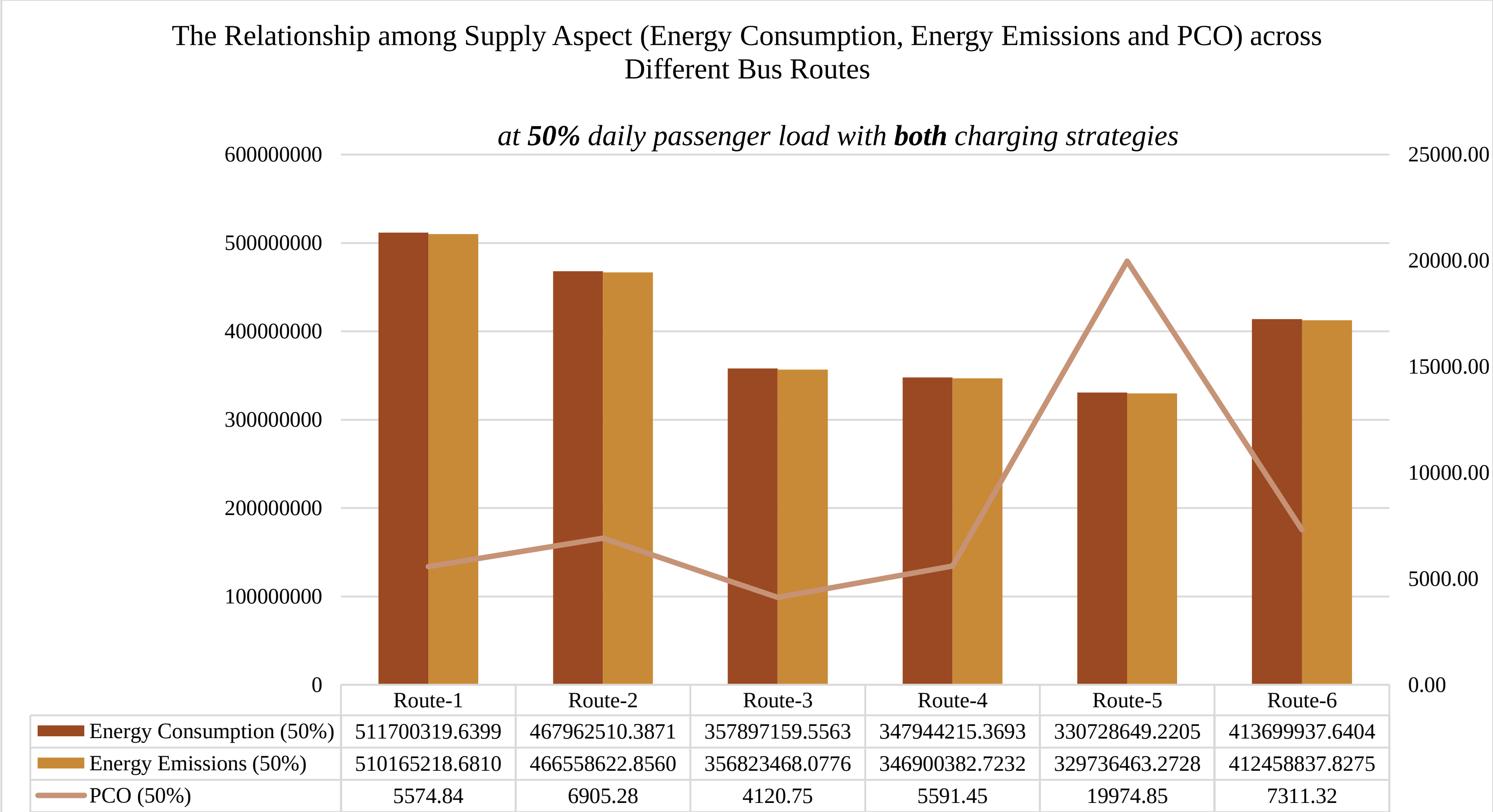
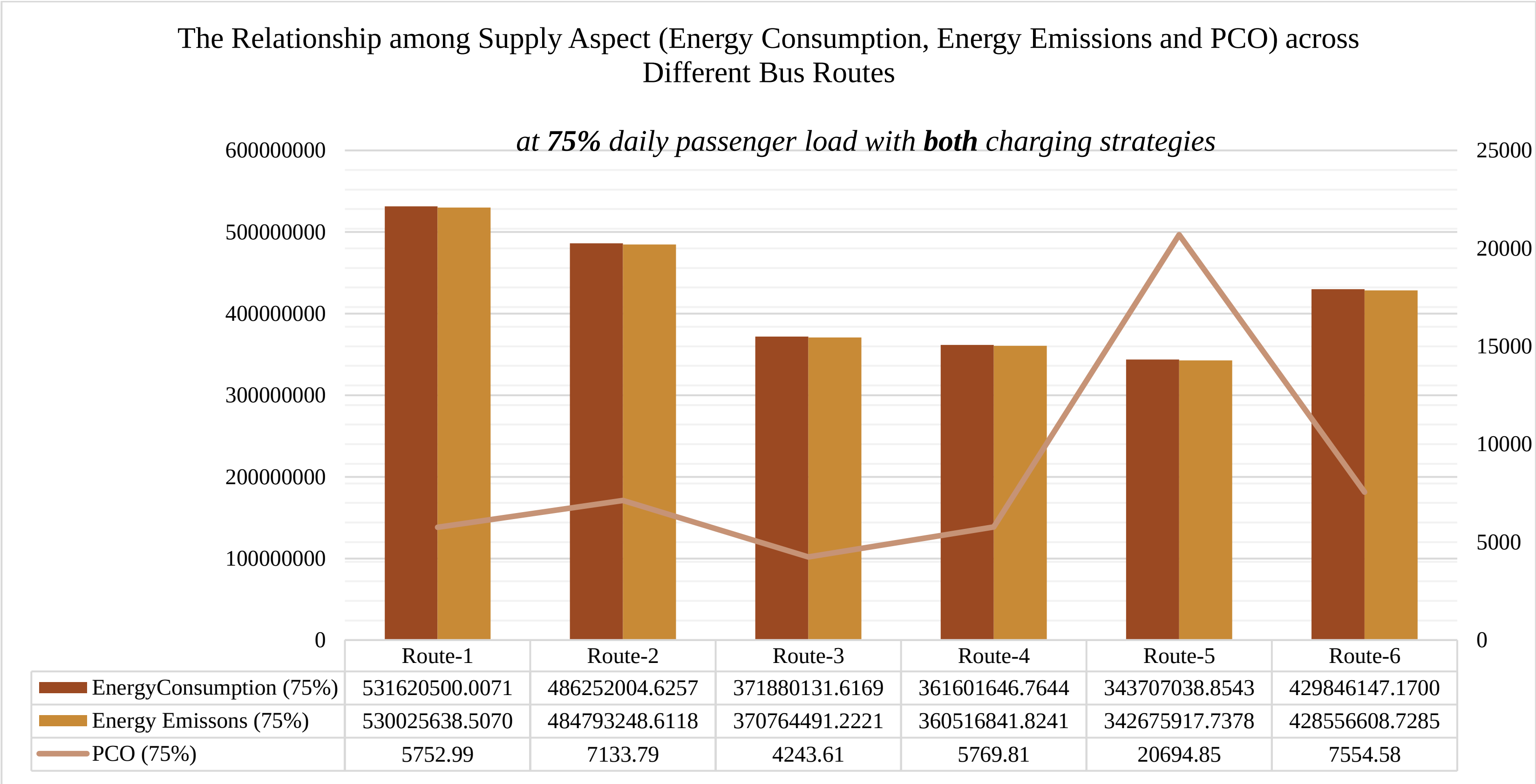


Figure 4.24: The Relationship among Supply Aspects (Energy Consumption, Energy Emissions and PCO) across Different Bus Routes at 25%, Daily Passenger Load with Both Charging Strategies.



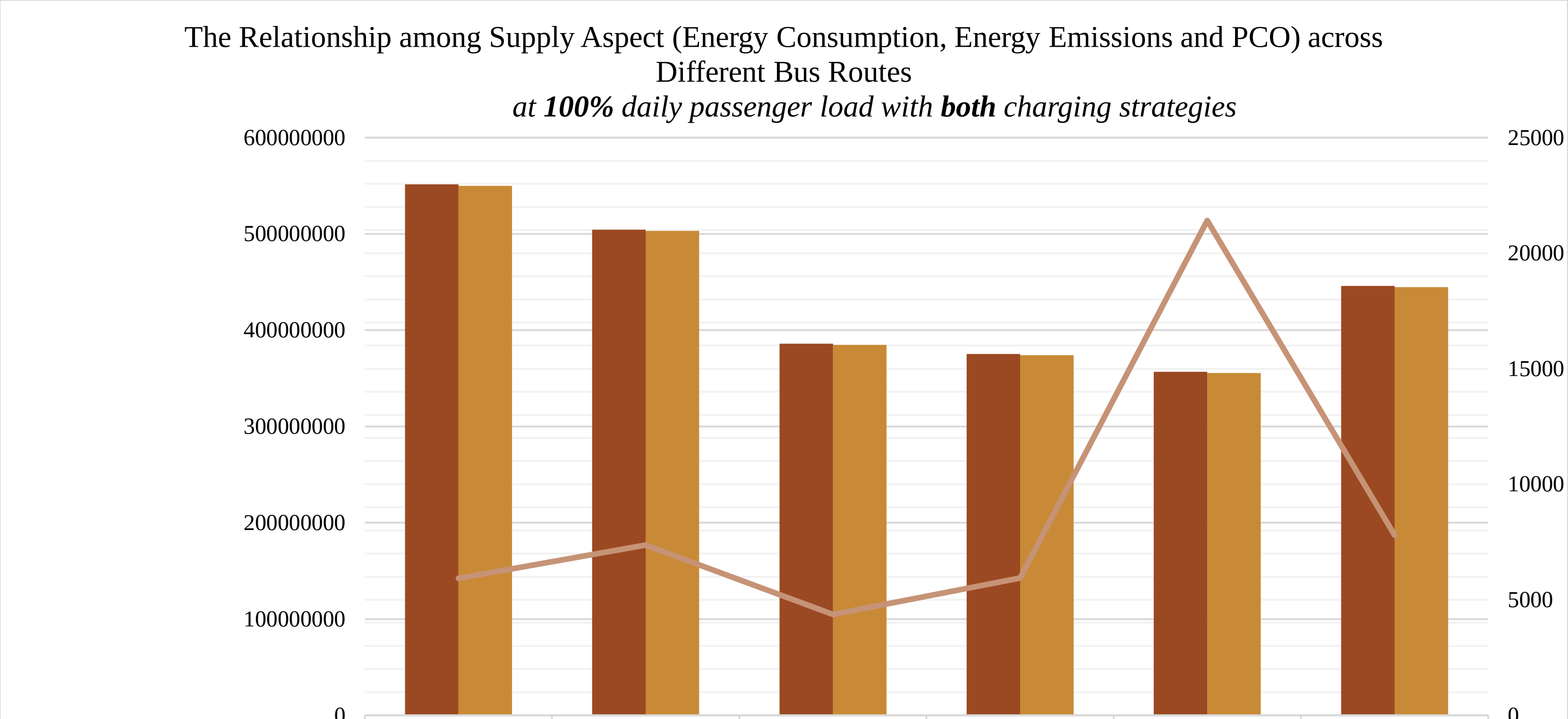
	Route-1	Route-2	Route-3	Route-4	Route-5	Route-6
Energy Consumption (50%)	511700319.6399	467962510.3871	357897159.5563	347944215.3693	330728649.2205	413699937.6404
Energy Emissions (50%)	510165218.6810	466558622.8560	356823468.0776	346900382.7232	329736463.2728	412458837.8275
PCO (50%)	5574.84	6905.28	4120.75	5591.45	19974.85	7311.32

Figure 4.25: The Relationship among Supply Aspects (Energy Consumption, Energy Emissions and PCO) across Different Bus Routes at 50% Daily Passenger Load with Both Charging Strategies.



	Route-1	Route-2	Route-3	Route-4	Route-5	Route-6
EnergyConsumption (75%)	531620500.0071	486252004.6257	371880131.6169	361601646.7644	343707038.8543	429846147.1700
Energy Emissons (75%)	530025638.5070	484793248.6118	370764491.2221	360516841.8241	342675917.7378	428556608.7285
PCO (75%)	5752.99	7133.79	4243.61	5769.81	20694.85	7554.58

Figure 4.26: The Relationship among Supply Aspects (Energy Consumption, Energy Emissions and PCO) across Different Bus Routes at 75% Daily Passenger Load with Both Charging Strategies.



	Route-1	Route-2	Route-3	Route-4	Route-5	Route-6
Energy Consumption (100%)	551540680.3924	504541498.8825	385863103.6993	375259078.1667	356685428.4945	445992356.7141
Energy Emissions (100%)	549886058.3512	503027874.3858	384705514.3882	374133300.9322	355615372.2091	444654379.6440
PCO (100%)	5931.15	7362.30	4366.47	5948.17	21414.84	7797.84

Figure 4.27: The Relationship among Supply Aspects (Energy Consumption, Energy Emissions and PCO) Across Different Bus Routes at 100% Daily Passenger Load with Both Charging Strategies.

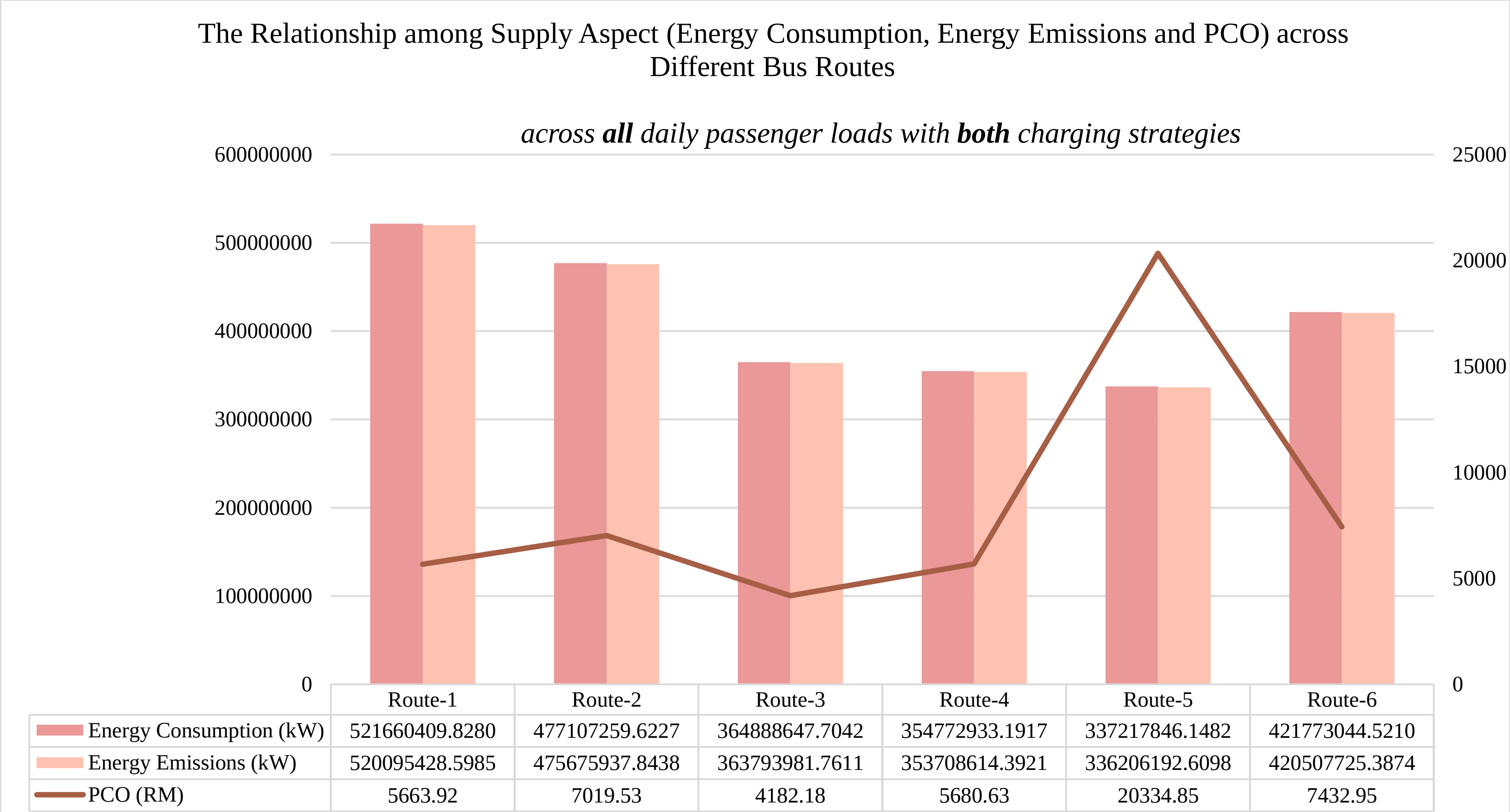
4.6.1.4 Scenario 13: All Daily Passenger Loads with Both Charging Strategies

As shown in Figure 4.28, Route-3 continuously maintains the lowest energy aspects, while Route-5 achieves the lowest PCO. When considering the overall supply aspects at all daily passenger loads and charging strategies, Route-3 emerges as the most recommended bus route for replacing CBs. Conversely, Route-5 ranks at the bottom with the least recommendation because of its high PCO. The intermediate rankings between these two routes are as follows: Route-4, Route-1, Route-2, and Route-6.

4.6.2 Weightage of Criteria

This section discusses the effect of the weightage assigned to each criterion in the fuzzy TOPSIS analysis on the selection of the most suitable bus route for BEB operations. Each criterion's weight reflects its influence on the overall decision, with PCO having the highest weight, indicating its significant role in the decision-making process. The overall PCO is rated as the most important criterion by six experts with daily passenger load following behind with an above-average weighting. Besides, energy consumption and energy emissions are assigned lower weights, occupying the last two positions in terms of the importance level collected from experts and as presented in Table 4.12.

As detailed in Appendix B, Route-1 and Route-2 exhibit higher frequencies compared to the other routes, with Route-3, Route-4, and Route-6 having equal frequencies and Route-5 having the lowest frequency. Given the scenario under the same passenger load factor, the daily passenger load for Route-1 and Route-2 will naturally be higher than for the other routes. Therefore, the operating bus routes with higher frequencies, that is Route-1 and Route-2, are prioritized based on demand aspects.



	Route-1	Route-2	Route-3	Route-4	Route-5	Route-6
Energy Consumption (kW)	521660409.8280	477107259.6227	364888647.7042	354772933.1917	337217846.1482	421773044.5210
Energy Emissions (kW)	520095428.5985	475675937.8438	363793981.7611	353708614.3921	336206192.6098	420507725.3874
PCO (RM)	5663.92	7019.53	4182.18	5680.63	20334.85	7432.95

Figure 4.28: The Relationship among Supply Aspects (Energy Consumption, Energy Emissions and PCO) across Different Bus Routes at All Daily Passenger Loads with Both Charging Strategies.

4.6.3 Summary

From the analysis, it is notable that the bus route rankings are influenced by a range of factors. The analysis which focuses on the supply aspects, suggests Route-3 as the recommendation for BEB operations due to its lowest PCO, while Route-5 is highlighted for its minimal energy consumption. However, when considering the combined aspects of energy consumption, emissions and PCO, Route-3 emerges as the most desirable route overall. Conversely, from a demand perspective, Route-1 and Route-2 are identified as the most favourable options. Given the contrasting results from different viewpoints, the weightage assigned by experts is crucial for prioritizing each criterion. This approach helps in determining the final ranking of each route based on both supply and demand aspects. As a result, Route-1 is recommended as it offers a balanced perspective across both supply and demand considerations.

4.7 Results Benchmarking and Comparison

Awasthi, Chauhan, and Omrani (2011) used the fuzzy TOPSIS method to develop a framework for selecting the most sustainable city for green transportation. This project applies the same evaluation method but to identify the most suitable bus routes and types in contributing to bus operations. While Emami, Song, and Khani (2022) employed the TOPSIS method to propose a similar idea to this project. Their evaluation used the traditional TOPSIS approach without incorporating fuzzy logic. Additionally, the influencing factors they considered differ from those in this project. Their focus was more on general aspects such as population and service frequency, whereas this project emphasizes macroeconomic factors, specifically energy and cost considerations. In summary, the results of this project successfully proposed a framework to assist bus operators in selecting the most suitable bus routes and types for implementing bus electrification.

To explore the potential for reducing energy consumption, emissions, and costs, two relevant papers are referenced. The reason for referencing the two previous papers is their analysis focus on small-sized transportation systems and the comparison of energy and cost aspects between CB and BE, whose findings may be beneficial to this project. According to Segar (2019), it was reported that the implementation of BEB may reduce CO_2 emissions by up to 132.52kg per bus trip along with a savings around 536.45kW of electricity. Kim and Hartmann (2022) concluded that while the initial costs of introducing EB may be competitive with CB. However, the growing fuel price and concern on reducing GHG emissions is likely to surpass that of CBs and widen the cost gap. This trend shows a positive impact on the adoption of EB, suggesting that it could be more cost-effective to implement EBs compared to CBs. Drawing from the findings of the two previous papers, they show the sign that this project also demonstrates the contribution to cutdown energy consumption, emissions, and costs.

4.8 Overall Summary

This chapter successfully identifies the most desirable bus route for BEB operations and the most favourable bus type for BEB operations for the case study of UTAR (Sungai Long campus). According to the results, Pelican Yutong e9 (bus type Y3) is considered the most suitable to replace CB on the most desirable bus route (Route-1) for passenger loads less than 22 and more than 33, while BYD eBus 13 (bus type Y1) is recommended for replacing CB on the same route for passenger loads in between 22 to 33. Additionally, the influential factors (energy consumption, energy emissions, PCO and passenger load factor) are found to be interrelated as the rankings of bus routes are determined not by a single criterion but by all criteria collectively. Notably, the weightage of each criterion also plays a crucial role in influencing the final rankings.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

In a nutshell, this project demonstrates a significant commitment to advancing sustainable public transportation by focusing on the development of a viable multi-criteria green fleet plan to support EB operations. By integrating both environmental and economic considerations, this project seeks to optimize the selection of electric buses and routes, contributing to a more sustainable and efficient transportation system. A key achievement of this project is the successful determination of a heterogeneous electric bus planning strategy, which supports a diverse range of operating conditions such as bus quantity and bus frequency.

To ensure that the proposed framework is both practical and adaptable to real-world scenarios, this project commenced with an extensive literature review aimed at identifying the current state of knowledge in the field of EB operations and sustainable transportation. The review was essential for understanding the work that has already been undertaken and to uncover areas that had not been sufficiently explored. To fill in the lacking knowledge, the project proposed a robust framework to tackle the complex MCDM problem within EB operations. This project was designed to evaluate various influencing factors critical to the operation of BEB, such as energy consumption, energy emissions, and the PCO. The formulation of these factors was meticulously selected to ensure accurate and reliable calculations at the first step. Following the establishment of the framework, a comprehensive data collection process was initiated. It involved gathering detailed information on bus route characteristics, such as route length, bus frequency and trip time as well as the specifications of each BEB, including passenger capacity, battery capacity and its curb weight. The data collection process, it allowed this project to make a comparative analysis among different BEB to assess the performance of different bus routes and identify which were most suitable for electrification.

Before conducting the evaluation, this project proceeded with the design and conduct of survey to experts whose valuable opinions were crucial in refining the evaluation. The survey aimed to gather weightages for various criteria, reflecting the relative importance of each factor in the decision-making process. These weightages were then integrated into the fuzzy TOPSIS method to rank the bus routes and identify the most suitable BEB for electric bus implementation. By considering both environmental and economic factors, the project ensured that the selected routes and bus types would not only minimize energy impact and maximize cost efficiency but also optimize passenger loads to enhance potential income for bus operators.

In practice, Route-1 stood out as the most desirable bus route for BEB operations. Further examination revealed that though Route-1 doesn’t exhibit the lowest energy and economic aspect, but it boasts the highest passenger load factor. That’s why it emerged as the most suitable bus route. Next, the Pelican Yutong e9 is identified as the most favourable option to replace CB on Route-1 for passenger loads below 22 and with two buses at passenger levels above 33, while the BYD eBus 13 is recommended for loads between 22 and 33 passengers. This project has made significant strides in advancing the field of sustainable public transportation by proposing a comprehensive and practical green fleet planning strategy. The results of this project hold the potential to inform future decisions in electric bus operations, contributing to the broader goal of reducing the environmental impact of public transportation while maintaining economic viability. The successful implementation of this strategy could serve as a model for other regions aiming to transition to greener, more sustainable public transport systems.

5.2 Recommendations For Future Work

Apparently, there are two limitations to this project. The primary concern lies in data collection, as the data may not fully reflect real-time scenarios since much of it was gathered online. As a result, the illustrative case study utilized data inputs from various sources. Consequently, the data inputs may represent real bus operating conditions to some extent and the results should be regarded as reference points, potentially applicable to specific situations rather than providing definitive conclusions. To address the issue mentioned above, future works are suggested to collect the data directly from real-time such as the bus travelling velocity.

Additionally, future research could benefit from exploring alternative evaluation tools (for example AHP and VIKTOR) beyond fuzzy TOPSIS and comparing their results. By incorporating multiple evaluation methods, bus operators can gain a more comprehensive understanding and produce more robust and reliable findings. This approach would allow for a comparison of results across different methods and thus offering a broader perspective and potentially leading to more valuable insights and persuasive conclusions.

REFERENCES

Abas, N., Kalair, A., Khan, N. and Kalair, A.R., 2017. Review of GHG emissions in Pakistan compared to SAARC countries. *Renewable and Sustainable Energy Reviews*, 80, pp.990-1016.

ACS, 2024. Sync R&D – The home of Malaysia's first electric buses, *ACS AsiaPac*. [Online] Available at: https://acsasiapac.com/index.php/in-the-news-k2/devs-nst-cbt/110-sync-rd-the-home-of-malaysia-s-first-electric-buses#:~:text=According%20to%20Azlan%2C%20the%20price,RM650k%20for%20a%20diesel%20bus [Accessed: 02 September 2024].

Adheesh, S.R., Vasisht, M.S. and Ramasesha, S.K., 2016. Air-pollution and economics: diesel bus versus electric bus. *Current Science*, 110(5), pp.858-862.

Ahmad, M.S., Zulkipli, Z.H., Batcha, W.A., Paimen, N.F., Faudzi, S.A.M., Othman, I. and Osman, M.R., 2017. An observational study on speeding among Malaysian express bus drivers. *Journal of the Society of Automotive Engineers Malaysia*, 1(2), pp. 94-102.

Al-Ogaili, A.S., Al-Shetwi, A.Q., Sudhakar Babu, T., Hoon, Y., Abdullah, M.A., Alhasan, A. and Al-Sharaa, A., 2021. Electric buses in Malaysia: Policies, innovations, technologies and life cycle evaluations. *Sustainability*, 13(21), p.11577.

Al-Ogaili, A.S., Ramasamy, A., Hashim, T.J.T., Al-Masri, A.N., Hoon, Y., Jebur, M.N., Verayiah, R. and Marsadek, M., 2020. Estimation of the energy consumption of battery driven electric buses by integrating digital elevation and longitudinal dynamic models: Malaysia as a case study. *Applied Energy*, 280, p.115873.

Amheka, A., Nguyen, H.T., Yu, K.D., Noach, R.M., Andiappan, V., Dacanay, V.J. and Aviso, K., 2022. Towards a low carbon ASEAN: an environmentally extended MRIO optimization model. *Carbon balance and management*, 17(1), p.13.

Apostolaki-Iosifidou, E., Codani, P. and Kempton, W., 2017. Measurement of power loss during electric vehicle charging and discharging. *Energy*, 127, pp. 730-742.

Asamer, J., Graser, A., Heilmann, B. and Ruthmair, M., 2016. Sensitivity analysis for energy demand estimation of electric vehicles, *Transportation Research Part D: Transport and Environment*, 46, pp. 182-199.

Awasthi, A., Chauhan, S.S. and Omrani, H., 2011. Application of fuzzy TOPSIS in evaluating sustainable transportation systems. *Expert systems with Applications*, 38(10), pp.12270-12280.

Azmi, M.Y., Junidah, R., Mariam, A.S., Safiah, M.Y., Fatimah, S., Norimah, A.K., Poh, B.K., Kandiah, M., Shariff, Z.M., Manan, W., Din, S.H.M. and Aris, T., 2009. Body mass index (BMI) of adults: Findings of the Malaysian Adult Nutrition Survey (MANS). *Malaysian journal of nutrition*. 15, pp. 97-119.

Bartłomiejczyk, M. and Kołacz, R., 2020. The reduction of auxiliaries power demand: The challenge for electromobility in public transportation, *Journal of Cleaner Production*, 252, p. 119776.

Basma, H. *Mansour, C., Haddad, M., Nemer, M. and Stabat, P*. 2022. Energy consumption and battery sizing for different types of electric bus service, *Energy*, 239, p. 122454.

Bayındırlı, C. and Çelik, M., 2018. The experimentally and numerically determination of the drag coefficient of a bus model, *International Journal of Automotive Engineering and Technologies*, 7(3), pp. 117-123.

Bellman, R.E. and Zadeh, L.A., 1970. Decision-making in a fuzzy environment. *Management Science*, 17(4), p. 141.

Berckmans, G., Messagie, M., Smekens, J., Omar, N., Vanhaverbeke, L. and Van Mierlo, J., 2017. Cost projection of state of the art lithium-ion batteries for electric vehicles up to 2030. *Energies*, 10(9), p. 1314.

Brander, M. and Davis, G., 2012. Greenhouse gases, CO2, CO2e, and Carbon: What do all these terms mean? *Econometrica*, [White Paper] 4 September. Available At: https://ecometrica.com/assets/GHGs-CO2-CO2e-and-Carbon-What-Do-These-Mean-v2.1.pdf [Accessed 18 March 2024].

Burnham, A., Gohlke, D., Rush, L., Stephens, T., Zhou, Y., Delucchi, M.A., Birky, A., Hunter, C., Lin, Z., Ou, S., Xie, F., Proctor, C., Wiryadinata, S., Liu, N., and Boloor, M., 2021. Comprehensive Total Cost of Ownership Quantification for Vehicles with Different Size Classes and Powertrains. [Technical Report] April. p. ANL/ESD-21/4 167399.

BYD, 2024. BYD eBus B13. *BYD Europe*. [Online]. Available at: https://bydeurope.com/byd-ebus-b13 [Accessed: 02 September 2024].

Cambell, M., 2008. The drivers of the levelized cost of electricity for utility-scale photovoltaics. *Sunpower*. [Technical Report] 14 August. Available at: http://large.stanford.edu/courses/2010/ph240/vasudev1/docs/sunpower.pdf [Accessed 15 April 2024].

Chong, C.H., Tan, W.X., Ting, Z.J., Liu, P., Ma, L., Li, Z. and Ni, W., 2019. The driving factors of energy-related CO2 emission growth in Malaysia: The LMDI decomposition method based on energy allocation analysis. *Renewable and Sustainable Energy Reviews*, 115, p.109356.

Ceder, A., 2007. Public transit planning and operation: theory, modelling and practice. *Elsevier*. [Book].

Correa, G., Muñoz, P., Falaguerra, T. and Rodriguez, C.R., 2017. Performance comparison of conventional, hybrid, hydrogen and electric urban buses using well to wheel analysis. *Energy*, 141, pp. 537-549.

Correa, G., Muñoz, P.M. and Rodriguez, C.R., 2019. A comparative energy and environmental analysis of a diesel, hybrid, hydrogen and Electric Urban Bus. *Energy*, 187, p. 115906.

David, 2020. Working days Selangor 2020. *EXCELNOTES*. [Online]. Available at: https://excelnotes.com/working-days-selangor-2020/ [Accessed: 05 September 2024].

David, 2021. Working days Selangor 2021. *EXCELNOTES*. [Online]. Available at: https://excelnotes.com/working-days-selangor-2021/ [Accessed: 05 September 2024].

David, 2022. Working days Selangor 2022. *EXCELNOTES*. [Online]. Available at: https://excelnotes.com/working-days-selangor-2022/ [Accessed: 05 September 2024].

David, 2023. Working days Selangor 2023. *EXCELNOTES*. [Online]. Available at: https://excelnotes.com/working-days-selangor-2023/ [Accessed: 05 September 2024].

David, 2024. Working days Selangor 2024. *EXCELNOTES*. [Online]. Available at: https://excelnotes.com/working-days-selangor-2024/ [Accessed: 05 September 2024].

David, 2025. Working days Selangor 2025. *EXCELNOTES*. [Online]. Available at: https://excelnotes.com/working-days-selangor-2025/ [Accessed: 05 September 2024].

Deakin, T., 2019. Electric coach on the road: Yutong's TCE12, *Routeone*. [Online] 14 August. Available at: https://www.route-one.net/operators/electric-coach-on-the-road-yutongs-tce12/ [Accessed: 02 September 2024].

Doucette, R.T. and McCulloch, M.D., 2011. Modeling the CO2 emissions from battery electric vehicles given the power generation mixes of different countries. *Energy Policy*, 39(2), pp. 803-811.

Duoba, M., 2013. Developing a utility factor for battery electric vehicles. *SAE International Journal of Alternative Powertrains*. 2(2), pp. 362-368.

Emami, B.D., Song, Y. and Khani, A., 2022. Prioritizing bus routes for electrification: GIS-based multi-criteria analysis considering operational, environmental, and social benefits and costs. *Transportation Research Record: Journal of the Transportation Research Board*, 2676(8), pp. 10-23.

EPA, 2024. Sources of Greenhouse Gas Emissions, *EPA*. [Online]. Available at: https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions#t1fn2 [Accessed 06 March 2024].

GOAUTO, 2024a. 10.5m electric bus. *GOAUTO*. [Online]. Available at: https://goautovan.my/bus-54-seater-10m-electric-bus/ [Accessed: 05 September 2024].

GOAUTO, 2024b. 10.7m electric bus. *GOAUTO*. [Online]. Available at: https://goautovan.my/bus-54-seater-10m-electric-bus/ [Accessed: 05 September 2024].

GOAUTO, 2024c. 12m electric bus. *GOAUTO*. [Online]. Available at: https://goautovan.my/bus-54-seater-10m-electric-bus/ [Accessed: 05 September 2024].

Hao, X., Ou, S., Lin, Z., He, X., Bouchard, J., Wang, H. and Li, L., 2022. Evaluating the current perceived cost of ownership for buses and trucks in China. *Energy*, 254(A), p. 124383.

Hao, X., Yuan, Y., Wang, H. and Ouyang, M., 2021. Plug-in hybrid electric vehicle utility factor in China cities: Influencing factors, empirical research, and energy and environmental application. *eTransportation*, 10, p. 100138.

Hwang, C.L. and Yoon, K., 1981. Multiple attribute decision making: Methods and applications - a state-of-the-art survey, *Lecture Notes in Economics and Mathematical Systems*, p. 186.

Intergovernmental Panel on Climate Change (IPCC), 2023a. Climate Change 2021 – The physical science basis: Working Group I contribution to the sixth assessment report of the intergovernmental panel on climate change. *Cambridge University Press*.

Intergovernmental Panel on Climate Change (IPCC), 2023b. Climate Change 2022 - Mitigation of climate change: Working Group III contribution to the sixth assessment report of the intergovernmental panel on climate change. *Cambridge University Press*.

Jahic, A., Eskander, M., Avdevičius, E. and Schulz, D., 2023. Energy consumption of battery- electric buses: Review of influential parameters and modelling approaches. *B&H Electrical Engineering*, 17(2), pp. 7-17.

JPJ, 2024. Garis panduan pengiraan kadar lesen kenderaan motor (lkm) bagi kenderaan elektrik. *JPJ*. [Online]. Available at: https://www.jpj.gov.my/en/web/main-site/kenderaan1-en/-

/knowledge_base/vehicle/lkm-rates-calculation-guidelines [Accessed: 05 September 2024].

Juan, A.A., Mendez, C.A., Faulin, J., De Armas, J. and Grasman, S.E., 2016. Electric vehicles in logistics and transportation: A survey on emerging environmental, strategic, and operational challenges. *Energies*, 9(2), pp. 1-21.

Kalghatgi, G. and Johansson, B., 2017. Gasoline compression ignition approach to efficient, clean and affordable future engines. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, 232(1), pp. 118-138.

Kim, H. and Hartmann, N., 2022. Total cost of ownership analysis of battery electric buses for public transport system in a small to midsize city. *17th IAEE European Conference.* [Conference Paper].

Keller, V., Lyseng, B., Wade, C., Scholtysik, S., Fowler, M., Donald, J., Palmer-Wilson, K., Robertson, B., Wild, P. and Rowe, A., 2019. Electricity system and emission impact of direct and indirect electrification of heavy-duty transportation. *Energy*, 172, pp. 740-751.

Köbberling V. and Wakker, P.P., 2005. An index of loss aversion. *Journal of Economic Theory*, 122(1), pp. 119-131.

Kumar, S., Kumar, S. and Barman, A.G., 2018. Supplier selection using fuzzy TOPSIS multi criteria model for a small scale steel manufacturing unit. *Procedia computer science*, 133, pp. 905-912.

Lajunen, A. and Lipman, T., 2016. Lifecycle cost assessment and carbon dioxide emissions of diesel, natural gas, hybrid electric, fuel cell hybrid and electric transit buses. *Energy*, 106, pp. 329-342.

Lajunen, A., 2014. Energy consumption and cost-benefit analysis of hybrid and electric city buses. *Transportation Research Part C: Emerging Technologies*, 38, pp. 1-15.

Lajunen, A., 2018. Lifecycle costs and charging requirements of electric buses with different charging methods. *Journal of Cleaner Production*, 172, pp. 56-67.

Lindsay, 2016. Buses and batteries: A rising sector, *Power Technology*. [Online] 30 May. Available at: https://www.power-technology.com/features/featurebuses-and-batteries-a-rising-sector-4904956/ [Accessed 08 March 2024].

Ma, X., Miao, R., Wu, X. and Liu, X., 2021. Examining influential factors on the energy consumption of electric and diesel buses: A data-driven analysis of large-scale public transit network in Beijing. *Energy*, 216, p. 119196.

Mahmoud, M., Garnett, R., Ferguson, M. and Kanaroglou, P., 2016. Electric buses: A review of alternative powertrains. *Renewable and Sustainable Energy Reviews*, 62, pp. 673-684.

Majumder, S., De, K., Kumar, P., Sengupta, B. and Biswas, P.K., 2021. Techno-commercial analysis of sustainable E-bus-based public transit systems: An Indian case study. *Renewable and Sustainable Energy Reviews*, 144, p. 111033.

Mao, F., Li, Z. and Zhang, K., 2021. A comparison of carbon dioxide emissions between battery electric buses and conventional diesel buses. *Sustainability*, 13(9), p. 5170.

Manzolli, J.A., Trovao, J.P. and Antunes, C.H., 2022. A review of electric bus vehicles research topics–Methods and trends. *Renewable and Sustainable Energy Reviews*, 159, p. 112211.

MRCagney, 2017. Electric Technology Transport Research Report. *Final Report*.

Mikhaylov, K., Tervonen, J. and Fadeev, D., 2012. Development of energy efficiency aware applications using commercial low power embedded systems. *Embedded Systems - Theory and Design Methodology*. 19. pp. 408-430.

Mikhaylov, A., Moiseev, N., Aleshin, K. and Burkhardt, T., 2020. Global climate change and greenhouse effect. *Entrepreneurship and Sustainability Issues*, 7(4), pp. 2897-2913.

Ming, Y., Long, E. and Zhang, Y., 2017. Feasibility analysis of building heating system based on thermal-economical evaluation. *Procedia Engineering*, 205, pp. 1557-1563.

Muñoz, P., Franceschini, E.A., Levitan, D., Rodriguez, C.R., Humana, T. and Perelmuter, G.C., 2022. Comparative analysis of cost, emissions and fuel consumption of diesel, natural gas, electric and hydrogen urban buses. *Energy Conversion and Management*, 257, p. 115412.

Nădăban, S., Dzitac, S. and Dzitac, I., 2016. Fuzzy TOPSIS: A general view. *Procedia Computer Science*, 91, pp. 823-831.

National Research Council, 2013. Transitions to alternative vehicles and fuels. The National Academies Press. [Book].

Pagliaro, M. and Meneguzzo, F., 2019. Electric bus: A critical overview on the dawn of its widespread uptake. *Advanced Sustainable Systems*, 3(6), p. 1800151.

Pelican, 2024a. Pelican E9. *Pelican.* [Online]. Available at: https://pelicanyutong.co.uk/vehicle/e9/ [Accessed: 02 September 2024].

Pelican, 2024b. Pelican E10. *Pelican.* [Online]. Available at: https://pelicanyutong.co.uk/vehicle/e10/ [Accessed: 02 September 2024].

Pelican, 2024c. Pelican E12. *Pelican.* [Online]. Available at: https://pelicanyutong.co.uk/vehicle/e12/ [Accessed: 02 September 2024].

Pelican, 2024d. E12 electric bus. The Most Widely Proven 12m zero emission bus. *Pelican.* [Online]. Available at: https://pelicanyutong.effective-test-space.co.uk/buses/e12-electric-bus/ [Accessed: 02 September 2024].

Pelican, 2024e. Pelican TCe12. *Pelican.* [Online]. Available at: https://pelicanyutong.co.uk/vehicle/tce12/ [Accessed: 02 September 2024].

Pertz, S., 2019. Malaysia's First Electric Bus. *ASIAN BUSES*. 19(3) [e-Magazine] pp. 28-31. Available at: https://asiantrucker.com/images/all_magazines/issue19.pdf [Accessed: 02 September 2024].

Pojani, D. and Stead, D., 2015. Sustainable urban transport in the developing world: beyond megacities. *Sustainability*, 7(6), pp. 7784-7805.

Potkány, M., Hlatká, M., Debnár, M. and Hanzl, J., 2018. Comparison of the lifecycle cost structure of electric and diesel buses. *NAŠE MORE,* 65(4), pp. 270-275.

RinggitPlus, 2024. Petrol price Malaysia live updates (ron95, ron97 & diesel). *RinggitPlus*. [Online]. Available at: https://ringgitplus.com/en/blog/petrol-credit-card/petrol-price-malaysia-live-updates-ron95-ron97-diesel.html [Accessed: 05 September 2024].

Ritchie, H., 2020. Cars, planes, trains: Where do CO2 emissions from transport come from? *Our World in Data*. [Online] 6 October. Available at: https://ourworldindata.org/co2-emissions-from-transport [Accessed 06 March 2024].

Ritchie, H. and Rosado, P., 2017. Fossil fuels. *Our World in Data*. [Online] October. Available at: https://ourworldindata.org/fossil-fuels [Accessed: 08 March 2024].

Ritchie, H., Rosado, P. and Roser, M., 2020. Breakdown of carbon dioxide, methane and nitrous oxide emissions by sector. *Our World in Data*. [Online] June. Available at: https://ourworldindata.org/emissions-by-sector [Accessed: 08 March 2024].

Rodrigues, A.L.P. and Seixas, S.R.C., 2022. Battery-electric buses and their implementation barriers: Analysis and prospects for Sustainability. *Sustainable Energy Technologies and Assessments*, 51, p. 101896.

Rosian, M.B., 2023. Experts: electric bus adoption still low due to high costs, *Bernama*, [Online] 27 December. Available at:

https://bernama.com/en/bfokus/news.php?environment&id=2257459 [Accessed 08 March 2024].

Roszkowska, E. and Wachowicz, T., 2015. Application of fuzzy TOPSIS to scoring the negotiation offers in ill-structured negotiation problems. *European Journal of Operational Research*, 242(3), pp. 920-932.

Ryan, A., 2024. Electric vehicle charging cable care: What you need to know. *Fleet News*. [Online] 19 March. Available at: https://www.fleetnews.co.uk/features/ev-charging-cable-care-what-you-need-to-know#:~:text=Energy%20loss%20when%20charging%20vehicles&text=In%20some%20instances%2C%20it%20is,the%20accuracy%20of%20telematics%20data [Accessed: 02 September 2024].

SAE China, 2020. Energy-saving and new energy vehicle technology roadmap 2.0 officially released. *China Society of Automotive Engineers*. [Online] 27 October. Available at: https://en.sae-china.org/a3967.html [Accessed: 02 September 2024].

Salary Expert, 2024. School bus driver average base salary. *Salary Expert*. [Online]. Available at: https://www.salaryexpert.com/salary/job/school-bus-driver/malaysia [Accessed: 05 September 2024].

Salih, M.M., Zaidan, B.B., Zaidan, A.A. and Ahmed, M.A., 2019. Survey on fuzzy TOPSIS state-of-the-art between 2007 and 2017. *Computers & Operations Research*, 104, pp. 207-227.

Segar, B., 2019. The optimization of electric buses in Iskandar Malaysia. [Master Thesis]. *Universiti Teknologi Malaysia.*

Sheth, A. and Sarkar, D., 2019. Life cycle cost analysis for electric vs. Diesel Bus Transit in an Indian scenario. *International Journal of Technology*, 10(1), p. 105.

Sirbiladze, G., Ghvaberidze, B., Matsaberidze, B. and Sikharulidze, A., 2017. Multi-objective emergency service facility location problem based on fuzzy TOPSIS. *Bulletin of the Georgian National Academy of Sciences*, 11(1), pp. 23-30.

SWITCH, 2024a. SWITCH Metrocity. *SWITCH.* [Online]. Available at: https://www.switchmobilityev.com/en/metrocity [Accessed: 05 September 2024].

SWITCH, 2024b. SWITCH e1. *SWITCH.* [Online]. Available at: https://www.switchmobilityev.com/switch-e1 [Accessed: 05 September 2024].

Teoh, L.E., Goh, S.Y. and Khoo, H.L., 2021. Environmental assessment and improvement strategies for electric bus operations. *ITM Web of Conferences*, 36, p. 04004.

Teoh, L.E., Goh, S.Y. and Khoo, H.L., 2021. Green assessment and improvement framework for electric bus operational system. *Jurnal Kejuruteraan*, 33(3), pp. 741-751.

Teoh, L.E., Khoo, H.L., Goh, S.Y. and Chong, L.M., 2018. Scenario-based electric bus operation: A case study of Putrajaya, Malaysia. *International Journal of Transportation Science and Technology*, 7(1), pp. 10-25.

The Star, 2023. Is less pollution worth the costs? *The Star*. [Online] 17 April. Available at: https://www.thestar.com.my/aseanplus/aseanplus-news/2023/04/17/is-less-pollution-worth-the-costs [Accessed: 05 September 2024].

Unacademy, 2022. Transformer efficiency. *UPSC CSE – GS.* [Online] Available at: https://unacademy.com/content/upsc/study-material/physics/transformer-efficiency/#:~:text=What%20is%20Transformer%20Efficiency%3F,about%2080%25%20to%2095%25 [Accessed: 05 September 2024].

Universiti Tunku Abdul Rahman, 2019. Bus Services. *Bus Services*. [Online] Available at: https://dgs.sl.utar.edu.my/Bus-Services.php [Accessed: 08 March 2024].

Wabe, J. S., and Coles, O. B., 1975. The short and long-run cost of bus transport in urban areas. *Journal of Transport Economics and Policy*, 9(2), pp. 127-140.

Wargula, Ł., Wieczorek, B. and Kukla, M., 2019. The determination of the rolling resistance coefficient of objects equipped with the wheels and suspension system – results of preliminary tests. *MATEC Web of Conferences*, 254, p. 01005.

Wong, I., 2022. EV charging Malaysia - Types of EV chargers. *CARPUT*. [Online]. Available at: https://carput.my/ev-charging-malaysia-types-of-ev-chargers/?srsltid=AfmBOorWVBvMnvZ1QR3_IxQkE0EForgnIuVbhV-obnT6lQKM-_NpCXwj [Accessed: 05 September 2024].

Xylia, M., Leduc, S., Laurent, A.B., Patrizio, P., Van Der Meer, Y., Kraxner, F. and Silveira, S., 2019. Impact of bus electrification on carbon emissions: The case of Stockholm. *Journal of Cleaner Production*, 209, pp. 74-87.

Yutong, 2021. Yutong E10 helps Poland with low-carbon travel. *Bus-News*. [Online] 3 Jun. Available at: https://bus-news.com/yutong-e10-helps-poland-with-low-carbon-travel/ [Accessed: 05 September 2024].

Zadeh, L.A., 1975. The concept of a linguistic variable and its application to approximate reasoning—I. *Information sciences*, 8(3), pp. 199-249.

Zhang, X., Nie, S., He, M. and Wang, J., 2021. Charging system analysis, energy consumption, and carbon dioxide emissions of battery electric buses in Beijing. *Case Studies in Thermal Engineering*, 26, p. 101197.

Zhou, B., Wu, Y., Zhou, B., Wang, R., Ke, W., Zhang, S. and Hao, J., 2016. Real-world performance of battery electric buses and their life-cycle benefits with respect to energy consumption and carbon dioxide emissions. *Energy*, 96, pp.603-613.

APPENDICES

Appendix A: Expert Survey Questionnaire.

Survey on A Viable Multi-Criteria Green Fleet Planning for Electric Bus Operations

Hello Sir/Madam,

I am pursuing a Bachelor of Science (Honours) in Applied Mathematics with Computing at Universiti Tunku Abdul Rahman (UTAR). My Final Year Project (FYP) entitled **"A Viable Multi-Criteria Green Fleet Planning for Electric Bus Operations"** aims to propose a viable multi-criteria green fleet planning in supporting electric bus operations by determining desirable operating routes for heterogeneous electric buses with environmental and economic considerations.

According to the Intergovernmental Panel on Climate Change (2023), greenhouse gas emissions are the primary contributors to climate change today, disrupting global climate patterns. Vehicle electrification, particularly through electric buses, represents a crucial step towards reducing carbon footprints traditionally associated with fossil fuels. Thus, the adoption of electric buses as a practical form of public transportation appears to be a commendable endeavour to promote environmentally friendly mobility (Doucette and McCulloch, 2011).

In this project, **four influential factors**, namely **energy consumption**, **energy emissions**, **cost**, and **passenger load factor** are incorporated in determining desirable bus routes for electric bus operations. Energy consumption is vital as it directly impacts the range and efficiency of electric buses. Energy emissions are crucial to enhance the environmental benefits of electric bus operations by reducing the amount of pollutants. Cost is a key factor to ensure the economic viability of the electric bus operations. And, the passenger load factor is essential to ensure the practicality of the bus routes in meeting the demand of passengers at a desired level of service. These influential factors are vital to ensure that the proposed electric bus operating network is efficient, sustainable, and cost-effective.

The main objective of this survey is to collect the experts' perceptions on the importance (weightage) of influential factors in determining desirable bus routes for electric bus operations. The perceptions and ratings of experts on the respective influential factors are crucial in shaping a sustainable and viable green fleet operating network for electric buses.

The participation of experts is greatly valued for the success of this project. Participation in the survey is voluntary and all responses are strictly used for academic and scientific research purposes only. All information provided will be kept private and confidential.

Please move on to the following section if you are willing to participate in this survey.
Note: Each respondent is allowed to participate in this survey only once.

References

Doucette, R.T. and McCulloch, M.D., 2011. Modeling the CO_2 emissions from battery electric vehicles given the power generation mixes of different countries. *Energy Policy*, *39*(2), pp. 803–811.

Intergovernmental Panel on Climate Change (IPCC), 2023. *Climate change 2021 – the Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, United States: Cambridge University Press.

Informed Consent

I agree to participate in this survey.

I understand the purpose and nature of this study and I am participating voluntarily.

Section 1: Expert Information

Please fill up the following:

Name:	
Gender:	
Age:	
Position/Title:	
Organisation/Institution:	
Years of Working Experience:	
Area of Expertise:	
Highest Academic Qualification:	
Professional Certification (if any):	
Email Address:	
Phone Number (optional):	

<u>Section 2: Expert Perception</u>

To determine desirable bus routes for electric bus operations, two primary aspects, namely supply and demand are of utmost importance. The supply aspect plays a key role in minimizing **energy consumption**, **energy emissions**, and **cost** for electric bus operations while the demand aspect targets maximizing **passenger load factor**.

These four influential factors (energy consumption, energy emissions, cost, and passenger load factor) are crucial in determining desirable routes for electric bus operations. The detailed descriptions of each influential factor are provided in the table below.

Influential Factor		Description
Supply	Energy Consumption	It refers to the total energy used to support electric bus operations (including mechanical energy, auxiliary energy, and energy loss in the charging system).
	Energy Emissions	It indicates the carbon dioxide (CO_2) emissions generated by electric bus operations.
	Cost	It refers to the perceived cost of ownership (PCO) that encompasses the relevant expenses associated with the operations of electric buses (including vehicle cost, insurance cost, energy cost, implicit cost, maintenance & repair costs, and taxes & fees).
Demand	Passenger Load Factor	It denotes the capacity utilization of electric buses (percentage of total number of onboard bus passengers).

The ratings of experts on each influential factor are required to quantify the importance (weightage) of the respective factor in determining desirable bus routes for electric bus operations. The following table shows the rating scales from 1 to 5 where **a higher value of scale signifies greater importance (weightage) of the influential factor in operating electric buses.**

Scale	Linguistic Term
1	Very Low
2	Low
3	Moderate
4	High
5	Very High

Please use tick (√) to choose the relevant scale (linguistic term) **in accordance with the expert perception of the anticipated importance (weightage) of each influential factor in operating electric buses.**

Influential Factor	Scale (Linguistic Term)				
	1 (Very Low)	2 (Low)	3 (Moderate)	4 (High)	5 (Very High)
Energy Consumption					
Energy Emissions					
Cost					
Passenger Load Factor					

Your precious contribution to this project is so much appreciated. Thank you!

For additional comments (if any), please email Wong Shong Xuan (email: nicholaswsx@1utar.my).

THE END

Appendix B: Bus Frequencies Schedule for UTAR Shuttle Bus Routes.

Bus Route	Bus Frequency Schedule				
	Monday	Tuesday	Wednesday	Thursday	Friday
Route-1	10	10	10	10	9
Route-2	10	10	10	10	9
Route-3	8	8	8	8	8
Route-4	8	8	8	8	8
Route-5	7	7	7	7	7
Route-6	8	8	8	8	8

Appendix C: UTAR Bus Route.

Below depicts the route map for six shuttle buses provided by UTAR.

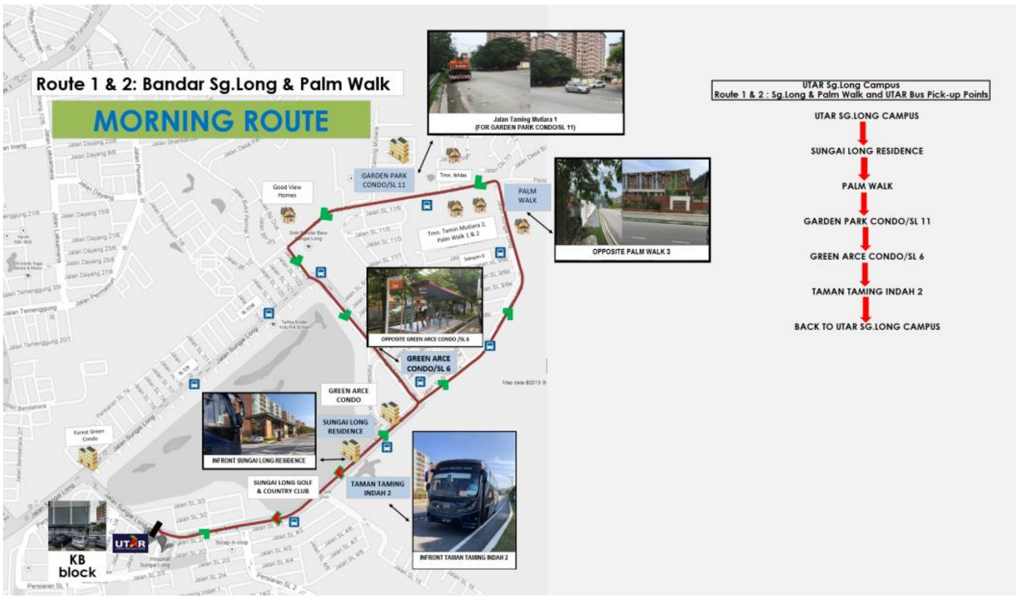


Figure C-1: Route-1: Bandar Sungai Long & Palm Walk (Morning Route)

Figure C-2: Route 2: Bandar Sungai Long & Palm Walk (Afternoon Route)

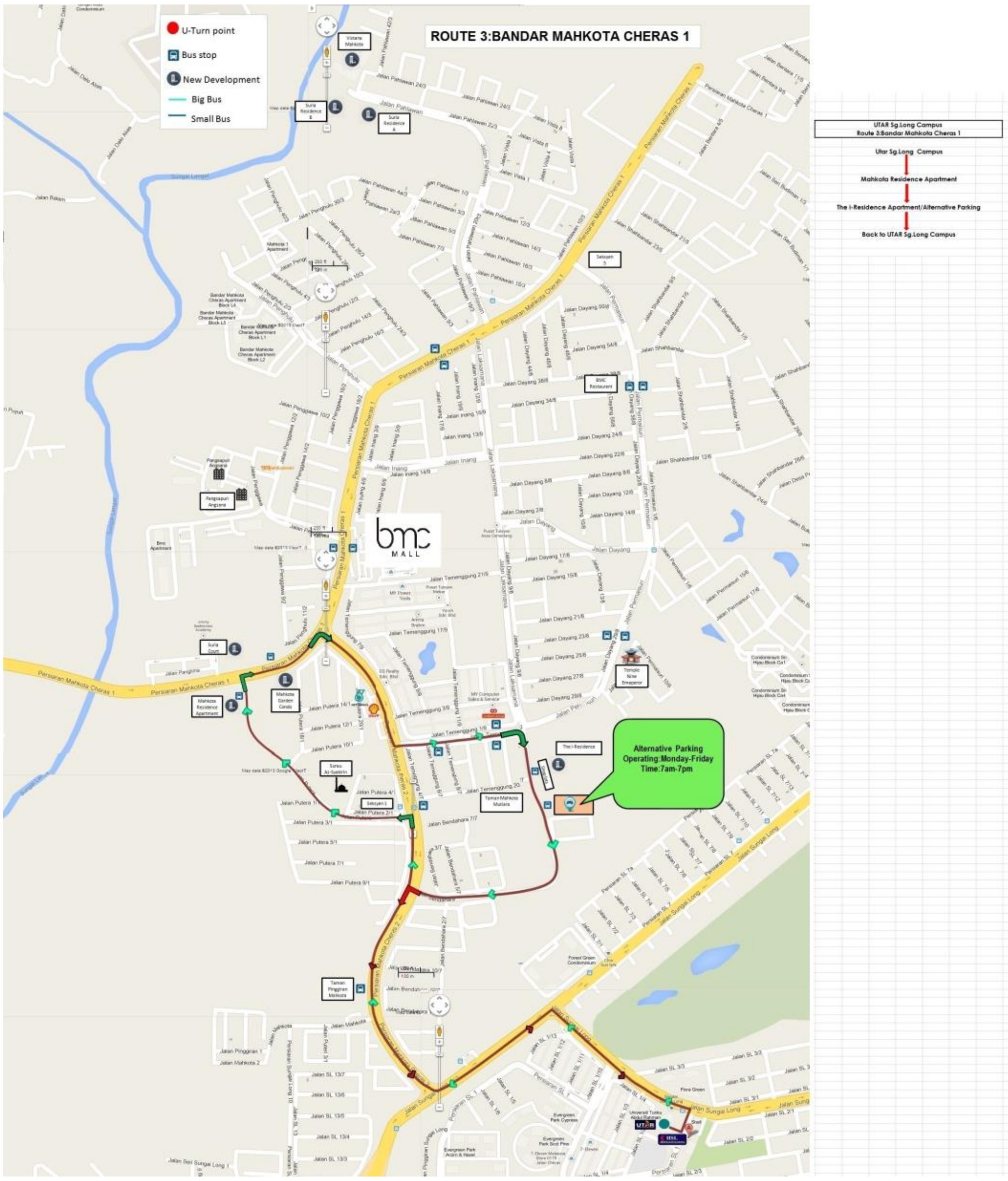


Figure C-3: Route 3: Bandar Mahkota Cheras 1

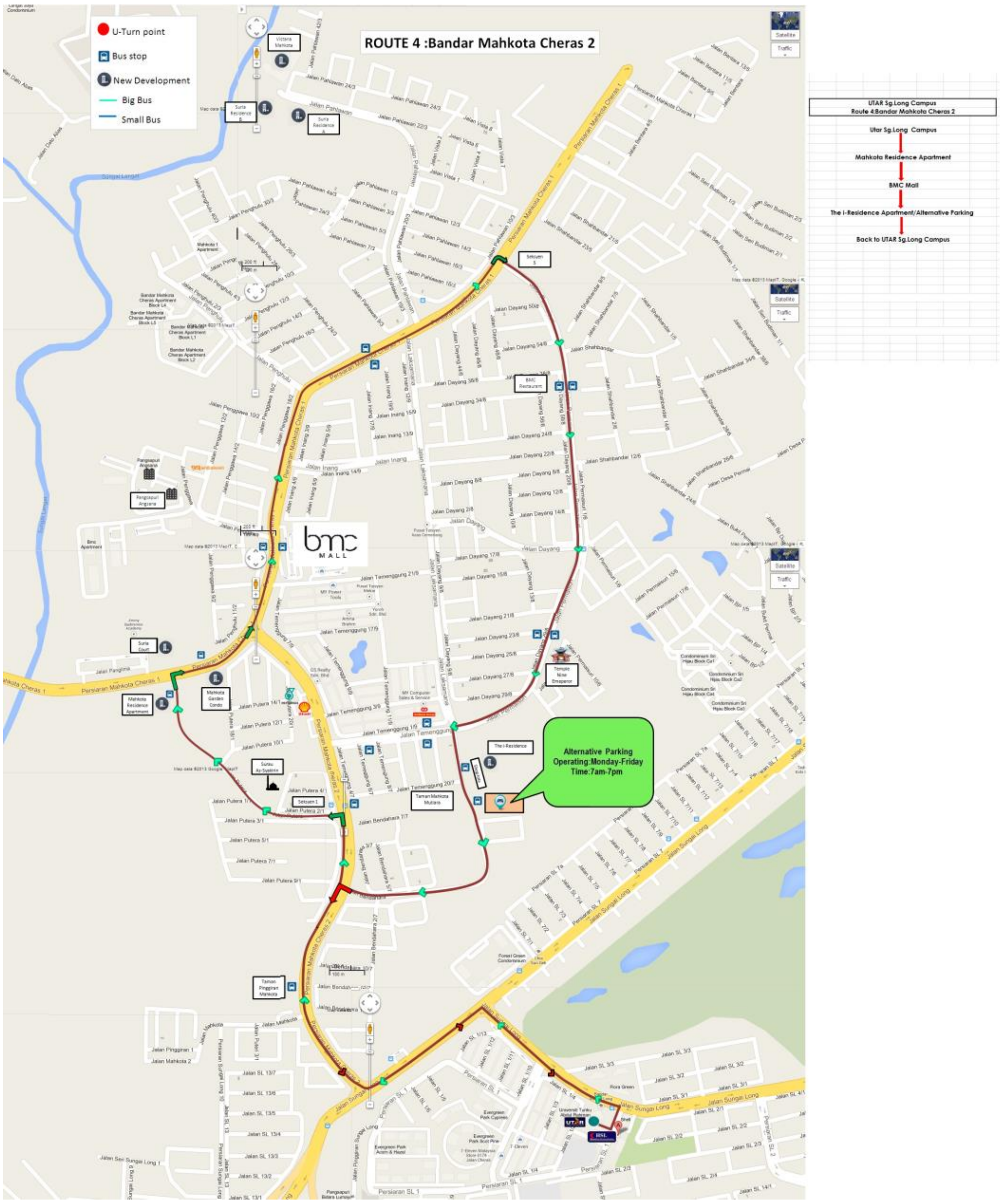


Figure C-4: Route 4: Bandar Mahkota Cheras 2

UTAR Sg.Long Campus
Route 5: KTM Serdang

UTAR SG.LONG CAMPUS

↓

OPPOSITE AEON CHERAS SELATAN (Bus Stop)

↓

INFRONT KTM SERDANG (Only for pickup)

↓

KG.BARU BALAKONG (Bus Stop)

↓

BACK TO UTAR CAMPUS

Figure C-5: Route 5: KTM Serdang Station

Figure C-6: Route 6: MRT Bukit Dukung

Appendix D: Python Code for Calculating Mechanical Energy.

```
#  Change the load factor (0.25,0.5,0.75,1.0) manually to get the total energy per bus type and bus route

import math

def firstPart(a, b, slope):
    result = (a + b * 1.0 * 62.65) * 9.80665 * 0.012 * math.cos(slope)
    return result

def secondPart(a, b, slope):
    result = (a + b * 1.0 * 62.65) * 9.80665 * math.sin(slope)
    return result

def uniLastPart(c):
    result = 0.5 * 1.2 * c * 0.645 * (66.2)**2
    return result

def accNdecThirdPart(c, v):
    result = 1.2 * c * 0.645 * v
    return result

def accNdecLastPart(a, b, mf, v):
    result = (a + b * 1.0 * 62.65 + mf) * v
    return result

def eUni(a, b, c, distance, slope):
    result = (0.9 / 3600) * (firstPart(a, b, slope) + secondPart(a, b, slope) + uniLastPart(c)) * distance
    return result

def eAcc(a, b, c, distance, slope, v, mf):
    result = (0.9 / 3600) * (firstPart(a, b, slope) + secondPart(a, b, slope) + accNdecThirdPart(c, v) + accNdecLastPart(a, b, mf, v)) * distance
    return result

def eDec(a, b, c, distance, slope, v, mf):
    result = (0.9 / 3600) * (firstPart(a, b, slope) + secondPart(a, b, slope) - accNdecThirdPart(c, v) + accNdecLastPart(a, b, mf, v)) * distance
    return result

def calculateAcceleration(initialVelocity, finalVelocity, distance, isAcceleration=True):
    if isAcceleration:
        acceleration = -(finalVelocity**2 - initialVelocity**3) / (2 * distance)
    else:
        acceleration = (finalVelocity**2 - initialVelocity**3) / (2 * distance)
    return acceleration
```

```
def energy(lengthsList, heightsList, mBEB, seat, frontalArea, mf):
    results = []

    for listIndex, (lengths, heights) in enumerate(zip(lengthsList, heightsList)):
        totalEnergy = 0
        for index in range(len(mBEB)):
            a = mBEB[index]
            b = seat[index]
            c = frontalArea[index]
            initialVelocity = finalVelocity = 66.2

            for i in range(len(lengths) - 1):
                deltaH = heights[i + 1] - heights[i]
                deltaD = lengths[i + 1] - lengths[i]

                slope = math.radians(math.atan(deltaH / deltaD))

                if deltaH > 0:
                    acceleration = calculateAcceleration(initialVelocity, 0, deltaD,
isAcceleration=True)
                    energy = eAcc(a, b, c, deltaD, slope, acceleration, mf)
                elif deltaH < 0:
                    acceleration = calculateAcceleration(0, finalVelocity, deltaD,
isAcceleration=False)
                    energy = eDec(a, b, c, deltaD, slope, acceleration, mf)
                else:
                    energy = eUni(a, b, c, deltaD, slope)

                totalEnergy += energy

            results.append({
                'a': a,
                'b': b,
                'c': c,
                'totalEnergy': totalEnergy,
            })

    return results

length = [[0,     0.1,    0.5,    1,      1.6,    1.94,   2.25,   3.1,
           3.73,  3.98,   4.06,   4.28,   5,      5.5,    6.15,   6.85,
           7],
          [0,     0.165,  0.715,  0.85,   1.8,    2.22,   3.05,   3.22,
           3.48,  4.46,   4.94,   5.25,   5.4,    5.59,   6.29,   6.89,
           7.46,  7.75,   7.83,   8.1,    8.3],
          [0,     0.165,  0.715,  1.05,   1.46,   1.59,   1.65,   1.7,
           1.72,  1.78,   1.83,   1.87,   1.92,   2.07,   2.75,   2.96,
           3.1,   3.5,    3.86,   3.96,   4.06,   4.35,   4.83,   4.89,
```

```
     5.19,   5.26,   5.38,   5.62,   6.36,   6.4,    6.49,   6.53,
     6.57,   6.66,   6.9],
    [0,      0.165,  0.715,  1.05,   1.46,   1.6,    1.65,   1.7,
     1.72,   1.79,   1.85,   1.88,   1.92,   2.07,   2.75,   2.95,
     3.17,   3.23,   3.29,   3.83,   4.18,   4.24,   4.48,   5.1,
     5.22,   5.56,   5.8,    5.86,   6.11,   6.2,    6.55,   6.98,
     7.04,   7.36,   7.41,   7.54,   7.78,   8.55,   8.66,   9],
    [0,      0.165,  0.715,  1.05,   1.32,   1.52,   1.61,   1.9,
     2.37,   3.07,   3.16,   3.3,    3.83,   4.04,   4.74,   5.18,
     5.5,    6.7,    6.73,   6.9,    7.46,   9.54,   9.98,   10.4,
     11.4,   12.4,   12.7,   12.8,   12.9,   13.4,   13.5,   13.7,
     14.3,   14.4,   14.6,   15.5,   16,     16.4,   18.6,   19,
     19.2,   19.3,   20.5,   20.9,   21.2,   21.9,   22,     22.1,
     22.7,   23,     23.3,   23.5,   24.5,   24.7,   25.2],
    [0,      0.165,  0.715,  1.05,   1.32,   1.52,   1.62,   1.93,
     2.4,    3.08,   3.18,   3.25,   3.33,   3.5,    3.68,   4.08,
     4.13,   4.18,   4.45,   4.55,   4.68,   4.96,   5.14,   5.24,
     5.59,   5.83,   5.91,   6.08,   6.18,   6.76,   7.29,   7.53,
     7.65,   7.79,   7.96,   9.29,   10.1,   10.3,   10.7,   11.1]]

height = [[70,   70,     73,     68,     79,     77,     84,     54,
     54,     57,     54,     54,     79,     68,     70,     67,
     70],
    [70,     70,     51,     51,     54,     54,     79,     77,
     84,     54,     54,     57,     55,     55,     79,     68,
     73,     69,     70,     67,     70,     70],
    [70,     70,     51,     46,     67,     73,     72,     74,
     73,     76,     73,     75,     72,     78,     51,     57,
     57,     71,     71,     69,     70,     78,     71,     73,
     56,     58,     46,     50,     69,     69,     67,     68,
     70,     67,     70],
    [70,     70,     51,     46,     67,     74,     72,     74,
     73,     76,     73,     74,     72,     78,     51,     57,
     57,     56,     57,     71,     60,     60,     53,     71,
     71,     79,     71,     73,     69,     70,     78,     72,
     73,     56,     57,     46,     50,     70,     67,     70],
    [70,     70,     51,     46,     46,     45,     46,     43,
     60,     36,     40,     35,     39,     35,     34,     35,
     33,     55,     51,     53,     40,     70,     61,     75,
     41,     41,     49,     43,     48,     42,     42,     41,
     44,     41,     42,     75,     61,     70,     40,     53,
     51,     56,     33,     37,     32,     58,     49,     61,
     48,     53,     46,     46,     70,     67,     70],
    [70,     70,     51,     46,     46,     45,     47,     43,
     60,     36,     40,     35,     36,     34,     34,     43,
     41,     42,     33,     32,     35,     42,     35,     37,
     34,     36,     34,     40,     36,     61,     48,     52,
     42,     49,     46,     81,     72,     70,     67,     70]]
```

```
mBEB = [17417.95, 13000, 9750, 13200, 13750, 13500, 10775, 11800, 12000,
13000, 17000]
seat = [45, 36, 24, 33, 39, 50, 28, 26, 37, 42, 17]
frontalArea = [8.415, 7.0395, 7.9739, 8.37675, 8.4915, 8.67, 7.75, 8.375, 9.2,
8.375, 8.0825]

mf = 5

results = energy(length, height, mBEB, seat, frontalArea, mf)

# for i, result in enumerate(results, start=1):
#     busType = (i - 1) // len(length) + 1
#     routeNumber = (i - 1) % len(length) + 1
#     print(f"Energy of Bus Type {busType} Bus Route-{routeNumber}:")
#     print(f"  Total Energy: {result['totalEnergy']:.2f}")

busTypeBusRoute = {i: [] for i in range(1, 12)}
for i, result in enumerate(results):
    busType = (i // len(length)) + 1
    routeNumber = (i % len(length)) + 1
    totalEnergy = result['totalEnergy']
    busTypeBusRoute[busType].append(f"Bus Route-{routeNumber}:
{totalEnergy:.2f}")

for busType, energies in busTypeBusRoute.items():
    print(f"Energy of Bus Type {busType}:")
    for energy in energies:
        print(f"  {energy}")
```

Appendix E: Slope Map of Each UTAR Bus Route

Below is the slope map of each bus route for six shuttle buses provided by UTAR.

Figure E-1: Slope Map of Route-1: Bandar Sungai Long & Palm Walk (Morning Route)

Figure E-2: Slope Map of Route-2: Bandar Sungai Long & Palm Walk (Afternoon Route)

Figure E-3: Slope Map of Route-3: Bandar Mahkota Cheras 1

Figure E-4: Slope Map of Route-4: Bandar Mahkota Cheras 2

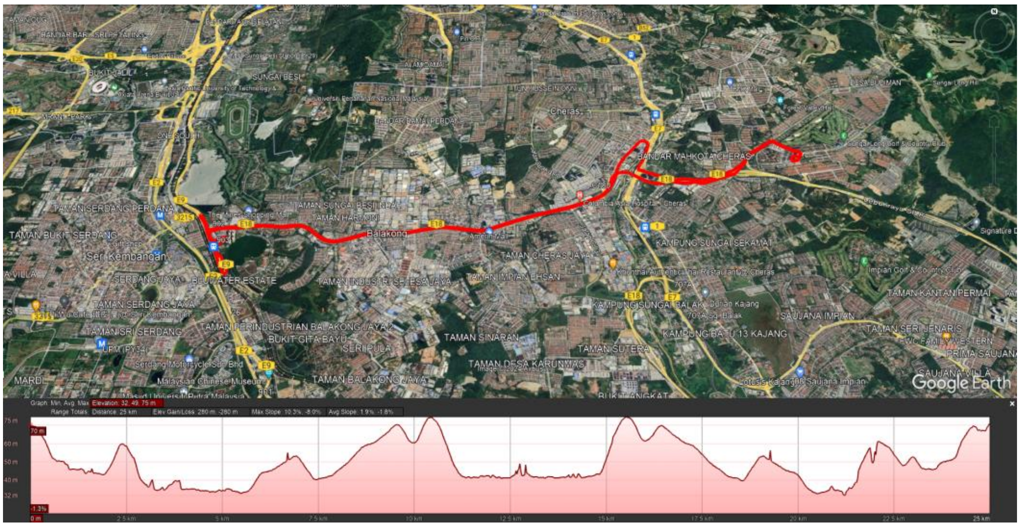


Figure E-5: Slope Map of Route-5: KTM Serdang Station

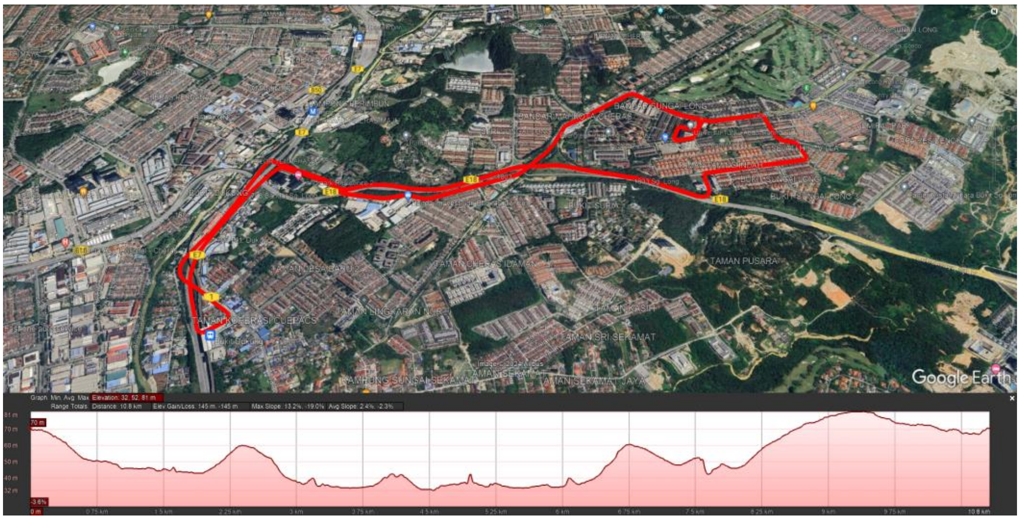


Figure E-6: Slope Map of Route 6: MRT Bukit Dukung

Appendix F: Location of Charging Stations.

*Remarks: The green pin marks the location of UTAR while the yellow pins represent the 10 nearest charging stations to UTAR that are included in this project.

Appendix G: Characteristics of Each Charging Station.

Platform		ChargeSini (2024)					chargeEV (2024)				
Location		BMC Mall	Parkland Residence	Raytech Sekamat Kajang	Vina Residency	Amerin Mall	Petronas Grand Saga 3	Petronas Grand Saga 2	Lotus Kajang	Auto Bavaria Balakong	KPJ Kajang Specialist Hospital
Number of Charging Piles	Slow		2	2	2	2			1	4	1
	Fast	2					1	1	2		
Power of Charging Pile (kW)	Slow		22	22	22	22			11	11.04	11.04
	Fast	40					24	24	50		
Charging Rate (RM/kW)	Slow		0.99	1.09	0.99	1.19			0.9	1.05	1.05
	Fast	1.47					1.3	1.3	1.5		
Time to and from UTAR (min)		16	18	18	36	28	16	24	26	30	31

Appendix H: Rankings of Scenario 5: 25%, 50%, 75%, or 100% Passenger Load Factors Considering Small or Big Bus Size with Either Slow or Fast Charging Strategies.

Table H-1: Ranking of bus at 25% passenger load factor considering small bus size with slow charging strategy.

Rankings of Buses at 25% Passenger Load Factor Considering Small Bus Size with Slow Charging Strategy												
Bus Type	Bus Route											
	Route-1		Route-2		Route-3		Route-4		Route-5		Route-6	
Y1	0.7159	2										
Y2											0.7640	1
Y3	0.8353	1	0.8353	1	0.9595	2	0.8353	1	0.9016	1	0.6945	2
Y4									0.7640	2		
Y5	0.5995	4										
Y6							0.7310	2				
Y7	0.6945	3										
Y8	0.3491	6	0.2633	3	1.0000	1	0.5956	3	0.6514	3	0.4143	3
Y9	0.4120	5										
Y10			0.7640	2								
Y11	0.1126	7	0.0971	4	0.0000	3	0.0000	4	0.0000	4	0.0000	4

Table H-2: Ranking of bus at 25% passenger load factor considering small bus size with fast charging strategy.

Rankings of Buses at 25% Passenger Load Factor Considering Small Bus Size with Fast Charging Strategy												
Bus Type	Bus Route											
	Route-1		Route-2		Route-3		Route-4		Route-5		Route-6	
Y1	1.0000	1										
Y2											0.7159	1
Y3	0.8353	2	0.8353	1	0.9595	2	0.8353	1	0.9016	1	0.6945	2
Y4									0.7159	3		
Y5	0.8071	3										
Y6							0.7159	2				
Y7	0.6945	4										
Y8	0.3491	6	0.3491	3	1.0000	1	0.6945	3	0.7539	2	0.5108	3
Y9	0.2280	7										
Y10			0.7640	2								
Y11	0.3800	5	0.0971	4	0.0000	3	0.0000	4	0.2841	4	0.0507	4

Table H-3: Ranking of bus at 25% passenger load factor considering big bus size with slow charging strategy.

Rankings of Buses at 25% Passenger Load Factor Considering Big Bus Size with Slow Charging Strategy												
Bus Type	Bus Route											
	Route-1		Route-2		Route-3		Route-4		Route-5		Route-6	
Y1	0.7159	2										
Y2											0.7640	1
Y3	0.8353	1	0.8353	1	0.9595	2	0.8353	1	0.9016	1	0.6945	2
Y4									0.7640	2		
Y5	0.5995	4										
Y6							0.7310	2				
Y7	0.6945	3										
Y8	0.3491	6	0.2633	3	1.0000	1	0.5956	3	0.6514	3	0.4143	3
Y9	0.4120	5										
Y10			0.7640	2								
Y11	0.1126	7	0.0971	4	0.0000	3	0.0000	4	0.0000	4	0.0000	4

Table H-4: Ranking of bus at 25% passenger load factor considering big bus size with fast charging strategy.

Rankings of Buses at 25% Passenger Load Factor Considering Big Bus Size with Fast Charging Strategy												
Bus Type	Bus Route											
	Route-1		Route-2		Route-3		Route-4		Route-5		Route-6	
Y1	1.0000	1										
Y2											0.7159	1
Y3	0.8353	2	0.8353	1	0.9595	1	0.8353	1	0.9016	1	0.6945	2
Y4									0.7159	3		
Y5	0.8071	3										
Y6							0.7159	2				
Y7	0.6945	4										
Y8	0.3491	6	0.3491	3	1.0000	1	0.6945	3	0.7539	2	0.5108	3
Y9	0.2280	7										
Y10			0.7640	2								
Y11	0.3800	5	0.0971	4	0.0000	3	0.0000	4	0.2841	4	0.0507	4

Table H-5: Ranking of bus at 50% passenger load factor considering small bus size with slow charging strategy.

Rankings of Buses at 50% Passenger Load Factor Considering Small Bus Size with Slow Charging Strategy												
Bus Type	Bus Route											
	Route-1		Route-2		Route-3		Route-4		Route-5		Route-6	
Y1	0.7159	2										
Y2											0.7310	1
Y3	0.8353	1	0.8353	1	0.9595	1	0.8353	1	0.9016	1	0.6945	2
Y4									0.7640	2		
Y5	0.5995	4										
Y6							0.7159	2				
Y7	0.6945	3										
Y8	0.3491	7	0.2633	3	0.8686	1	0.5956	3	0.6514	3	0.4143	3
Y9	0.4120	5										
Y10			0.7640	2								
Y11	0.1126	7	0.0971	4	0.0000	3	0.0000	4	0.0000	4	0.0000	4

Table H-6: Ranking of bus at 50% passenger load factor considering small bus size with fast charging strategy.

Rankings of Buses at 50% Passenger Load Factor Considering Small Bus Size with Fast Charging Strategy												
Bus Type	Bus Route											
	Route-1		Route-2		Route-3		Route-4		Route-5		Route-6	
Y1	1.0000	1										
Y2											0.7159	1
Y3	0.8353	2	0.8353	1	0.9595	1	0.8353	1	0.9016	1	0.6945	2
Y4									0.7159	3		
Y5	0.8071	3										
Y6							0.7159	2				
Y7	0.6945	4										
Y8	0.3491	6	0.3491	3	1.0000	1	0.6945	3	0.7539	2	0.5108	3
Y9	0.2280	7										
Y10			0.7640	2								
Y11	0.3800	5	0.0971	4	0.0000	3	0.0000	4	0.2841	4	0.0507	4

Table H-7: Ranking of bus at 50% passenger load factor considering big bus size with slow charging strategy.

Rankings of Buses at 50% Passenger Load Factor Considering Big Bus Size with Slow Charging Strategy												
Bus Type	Bus Route											
	Route-1		Route-2		Route-3		Route-4		Route-5		Route-6	
Y1	0.7159	2										
Y2											0.7159	1
Y3	0.7721	1	0.7721	1	0.7721	1	0.7721	1	0.6375	2	0.6375	2
Y4									0.7159	1		
Y5	0.5995	4										
Y6							0.7159	2				
Y7	0.6375	3	0.3523	3	0.2279	3	0.2026	4	0.3256	4	0.2633	4
Y8	0.2841	6	0.0507	4	0.6187	2	0.5420	3	0.4851	3	0.1472	4
Y9	0.4120	5										
Y10			0.7159	2								
Y11												

Table H-8:Ranking of bus at 50% passenger load factor considering big bus size with fast charging strategy.

Rankings of Buses at 50% Passenger Load Factor Considering Big Bus Size with Fast Charging Strategy												
Bus Type	Bus Route											
	Route-1		Route-2		Route-3		Route-4		Route-5		Route-6	
Y1	1.0000	1										
Y2											0.7159	1
Y3	0.7721	3	0.7721	1	0.7721	2	0.7721	1	0.6375	3	0.6375	2
Y4									0.7159	1		
Y5	0.8071	2										
Y6							0.7159	2				
Y7	0.6375	4	0.1624	4	0.2279	3	0.0157	4	0.4159	4	0.0815	4
Y8	0.2841	5	0.2841	3	0.9016	1	0.6375	3	0.6945	2	0.3800	3
Y9	0.2280	6										
Y10			0.7640	2								
Y11												

Table H-9: Ranking of bus at 75% passenger load factor considering small bus size with slow charging strategy.

Rankings of Buses at 75% Passenger Load Factor Considering Small Bus Size with Slow Charging Strategy												
Bus Type	Bus Route											
	Route-1		Route-2		Route-3		Route-4		Route-5		Route-6	
Y1	0.7159	2										
Y2											0.7159	1
Y3	0.7721	1	0.7721	1	0.7721	1	0.7721	1	0.6375	2	0.6375	2
Y4									0.7159	1		
Y5	0.5701	4										
Y6							0.7159	2				
Y7	0.6375	3	0.3523	3	0.2279	3	0.2026	4	0.3256	4	0.2633	4
Y8	0.2841	6	0.0507	4	0.6339	2	0.5420	3	0.4851	3	0.1472	4
Y9	0.4120	5										
Y10			0.7159	2								
Y11												

Table H-10: Ranking of bus at 75% passenger load factor considering small bus size with fast charging strategy.

Rankings of Buses at 75% Passenger Load Factor Considering Small Bus Size with Fast Charging Strategy												
Bus Type	Bus Route											
	Route-1		Route-2		Route-3		Route-4		Route-5		Route-6	
Y1	1.0000	1										
Y2											0.7159	1
Y3	0.7721	3	0.7721	1	0.7721	2	0.7721	1	0.6375	3	0.6375	2
Y4									0.7159	1		
Y5	0.8071	2										
Y6							0.7159	2				
Y7	0.6375	4	0.1624	4	0.2279	3	0.0157	4	0.4159	4	0.1163	4
Y8	0.2841	5	0.2841	3	0.9016	1	0.6375	3	0.6945	2	0.3800	3
Y9	0.2280	6										
Y10			0.7640	2								
Y11												

Table H-11: Ranking of bus at 75% passenger load factor considering big bus size with slow charging strategy.

Rankings of Buses at 75% Passenger Load Factor Considering Big Bus Size with Slow Charging Strategy												
Bus Type	Bus Route											
	Route-1		Route-2		Route-3		Route-4		Route-5		Route-6	
Y1	0.8151	1										
Y2	0.6116	2	0.5961	2	1.0000	1	0.4381	2	1.0000	1	1.0000	1
Y3												
Y4	0.5388	4	0.0000	4	0.0000	3	0.0000	4	0.0000	3	0.7721	2
Y5	0.6871	2										
Y6							1.0000	1				
Y7												
Y8												
Y9	0.2703	5										
Y10			1.0000	1								
*Y11	0.2397	6	0.4164	3	0.4721	2	0.4164	3	0.4721	2	0.0660	3
Remarks: * indicates two buses per trip												

Table H-12: Ranking of bus at 75% passenger load factor considering big bus size with fast charging strategy.

Rankings of Buses at 75% Passenger Load Factor Considering Big Bus Size with Fast Charging Strategy												
Bus Type	Bus Route											
	Route-1		Route-2		Route-3		Route-4		Route-5		Route-6	
Y1	1.0000	1										
Y2	0.6657	3	0.7616	2	1.0000	1	0.6696	2	1.0000	1	1.0000	1
Y3												
Y4	0.3253	4	0.0000	4	0.0000	3	0.0000	4	0.0000	3	0.4879	2
Y5	0.7307	2										
Y6							1.0000	1				
Y7												
Y8												
Y9	0.0727	6										
Y10			1.0000	1								
*Y11	0.2689	5	0.4302	3	0.4047	2	0.4302	3	0.5620	2	0.2633	3
Remarks: * indicates two buses per trip												

Table H-13: Ranking of bus at 100% passenger load factor considering small bus size with slow charging strategy.

Rankings of Buses at 100% Passenger Load Factor Considering Small Bus Size with Slow Charging Strategy												
Bus Type	Bus Route											
	Route-1		Route-2		Route-3		Route-4		Route-5		Route-6	
Y1	0.7159	1										
Y2											0.7159	1
Y3												
Y4	0.5956	4	0.5010	2	0.2909	3	0.1779	4	0.7159	1	0.6796	2
Y5	0.5995	3										
Y6							0.7159	1				
Y7	0.6375	2	0.3800	3	0.3491	2	0.2841	3	0.3491	3	0.2841	4
Y8	0.2841	6	0.2841	4	0.7721	1	0.6375	2	0.5420	2	0.3800	3
Y9	0.4450	5										
Y10			0.7159	1								
Y11												

Table H-14: Ranking of bus at 100% passenger load factor considering small bus size with fast charging strategy.

Rankings of Buses at 100% Passenger Load Factor Considering Small Bus Size with Fast Charging Strategy												
Bus Type	Bus Route											
	Route-1		Route-2		Route-3		Route-4		Route-5		Route-6	
Y1	1.0000	1										
Y2											1.0000	1
Y3												
Y4	0.4414	4	0.5010	2	0.2909	3	0.1624	4	0.7159	1	0.6796	2
Y5	0.8071	2										
Y6							1.0000	1				
Y7	0.6375	3	0.3800	3	0.3491	2	0.2841	3	0.3491	3	0.2841	4
Y8	0.2841	5	0.2841	4	0.7721	1	0.6375	2	0.6375	2	0.3800	3
Y9	0.1624	6										
Y10			1.0000	1								
Y11												

Table H-15: Ranking of bus at 100% passenger load factor considering big bus size with slow charging strategy.

Rankings of Buses at 100% Passenger Load Factor Considering Big Bus Size with Slow Charging Strategy												
Bus Type	Bus Route											
	Route-1		Route-2		Route-3		Route-4		Route-5		Route-6	
Y1	0.5693	2	0.5693	2	0.5693	2	0.5693	2	0.5693	2	0.5693	2
Y2												
Y3												
Y4												
Y5												
Y6	0.4307	3	0.4307	3	0.4307	3	0.4307	3	0.4307	3	0.4307	3
Y7												
Y8												
Y9												
Y10												
*Y3	0.6867	1	0.6867	1	0.6867	1	0.6867	1	0.6867	1	0.6867	1
Remarks: * indicates two buses per trip												

Table H-16: Ranking of bus at 100% passenger load factor considering big bus size with fast charging strategy.

Rankings of Buses at 100% Passenger Load Factor Considering Big Bus Size with Fast Charging Strategy												
Bus Type	Bus Route											
	Route-1		Route-2		Route-3		Route-4		Route-5		Route-6	
Y1	0.5122	2	0.5122	2	0.5122	2	0.5122	2	0.5122	2	0.5122	2
Y2												
Y3												
Y4												
Y5												
Y6	0.4878	3	0.4878	3	0.4878	3	0.4878	3	0.4878	3	0.4878	3
Y7												
Y8												
Y9												
Y10												
*Y3	0.6371	1	0.6371	1	0.6371	1	0.6371	1	0.6371	1	0.6371	1
Remarks: * indicates two buses per trip												