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# Life-Cycle Environmental and Economic Impacts of Alternative Fuel Buses

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## Abstract

This study undertook a comprehensive analysis of the eco-efficiency and economic viability of various city buses, focusing on their environmental impact and life cycle costs. Using Life Cycle Assessment (LCA), the environmental footprints of buses, considering their type and recycling country, were assessed. Results highlighted the generally lower environmental impacts of Compressed Natural Gas (CNG) buses compared to diesel and electric buses. Furthermore, Life Cycle Cost (LCC) evaluations showed diesel buses as the least economical, with Chinese CNG buses emerging as the most cost-effective over their lifespan. Additional analysis using the PCA-DEA model indicated the superior efficiency of certain bus units, especially both the Chinese CNG recycled in China and India. Sensitivity analysis further revealed that environmental categories with higher sensitivity ratios can achieve complete efficiency with modest improvements. Overall, the findings suggest that CNG buses, particularly those from China, present an eco-friendly and economically sustainable choice for urban transportation.

## Keywords

Life Cycle Assessment, Principal component analysis, Data envelopment analysis, Sustainable Transportation

# 1. Introduction

In our quest for a green, equitable future, the spotlight is on sustainability and public transportation's pivotal role. Compared to solo driving, public transport stands out as a beacon of sustainable development, markedly reducing greenhouse gas emissions and the carbon footprint. Beyond environmental benefits, it drives holistic urban planning, boosts public health, and enhances life quality (Ercan et al., 2016). The U.S. Department of Transportation notes that heavy rail systems emit 76% less greenhouse gas than cars, with buses recording a 33% reduction (H. Fan et al., 2023) .Although many view public transportation as a key solution for climate issues—given its prevalence in many cities—it needs astute planning to optimize resource use and achieve emission reduction goals. Affordable, effective, and eco-friendly public transport can save resources, purify the air, trim our environmental footprint, and facilitate access to jobs and education, fostering economic advancement. Alternative fuels, gradually replacing conventional ones in public perception, find a major application in public transit (Sandaka et al., 2023). These fuels hold immense promise, particularly for buses and shuttles designed for multiple passengers. The increasing allure of alternative fuel buses in recent research underscores their potential to curtail emissions and amplify sustainability. These buses, deriving energy from sources like electricity, natural gas, biodiesel, and hydrogen, each have unique ecological merits, spanning carbon dioxide emission cuts to pollution control.

Electric buses, emitting no harmful gases, often stand out as the pinnacle of eco-friendly, cost-efficient public transit. Deploying such buses paves the way for sustainable public transport, cutting down energy use and greenhouse gas emissions while ensuring an efficient, economical transit mechanism. Though their initial costs are higher than conventional buses, the reduced fuel and maintenance expenses across their lifespan make alternative fuel buses a worthy investment for transport agencies. Given the myriad benefits of alternative fuel buses—encompassing environmental advantages, cost savings, and their sustainability potential—this study delves into the environmental repercussions of different bus types operating in Qatar's public transport. Melding Life Cycle Assessment (LCA) with principal component analysis (PCA) and data envelopment analysis (DEA), it evaluates six-city bus brands. The calculated eco-efficiency scores reflect the balance between environmental impacts and life cycle cost assessment (LCC) outcomes. The research encompasses seven key environmental indicators, focusing on three bus types—compressed natural gas (CNG), diesel, and electric. The paper is outlined thus: An initial literature review identifies vital research voids. Subsequent sections detail the adopted research methodologies, present LCA results for the seven environmental indicators, the LCC analysis, and the eco-efficiency scores of the studied buses. Concluding remarks encapsulate the research's primary objectives and discoveries.

## 1.1 Objectives

Objective 1: Integration with Advanced Analytical Techniques

- To incorporate PCA to reduce the dimensionality of the environmental and cost data, thereby identifying the most significant variables influencing eco-efficiency.
- To apply DEA to derive eco-efficiency scores for each bus brand by comparing their environmental impact with their life cycle cost outcomes.
- To understand the trade-offs and interdependencies between various bus types' environmental impact and associated costs.

Objective 2: Recommendation and Policy Implication

- To provide a ranking of the selected city bus brands based on their eco-efficiency scores, highlighting those with the best balance between environmental performance and cost.
- To propose actionable recommendations for stakeholders, policymakers, and public transport operators in Qatar, emphasizing environmentally-friendly and cost-effective options.
- To suggest future research areas and potential improvements in Qatar's public transport ecosystem, emphasizing sustainable practices and technologies.

By achieving these objectives, the study aims to provide a comprehensive understanding of the environmental repercussions of different bus types in Qatar's public transport system and guide the transition towards more sustainable and cost-effective solutions.

## 2. Literature Review

The Life Cycle Assessment method, as well as the PCA–DEA model, have been proven to be useful in the area of sustainable transport for the purpose of finding solutions to a variety of issues(Miškić et al., 2022). The Life Cycle Assessment (LCA) has become an essential tool for determining the environmental effects that are caused by products, services, or activities throughout the course of their whole life cycle (Jakub et al., 2022; Nuri C. Onat et al., 2019). The LCA technique considers a wide variety of environmental consequences, ranging from raw material acquisition to ultimate disposal of a product (Guinée et al., 2011; Nuri C. Onat et al., 2017, 2019). The efficacy of this strategy has been recognized across various industries, including manufacturing (Kucukvar et al., 2015, 2016), energy (Kucukvar et al., 2017) (Shaikh et al., 2017), and agriculture (J. ; Fan et al., 2022); however, its application in the transportation industry (Elagouz et al., 2022; Nuri Cihat Onat et al., 2016), notably in evaluating electric vehicles (Bartolozzi et al., 2013), has been especially noteworthy. Parallel to LCA, Life Cycle Costing (LCC) offers a comprehensive financial perspective, capturing costs from initial investments to operational phases and culminating at the end-of-life phase (Menegaldo et al., 2023). Decision-makers leverage LCC to enhance the economic bearings of a system's life cycle (Toniolo et al., 2020). Broadening the spectrum of LCC reveals three variants: conventional LCC, environmental LCC, and societal LCC (David Hunkeler, 2008; Menegaldo et al., 2023). A harmonization of LCA and LCC techniques presents a cohesive framework that amalgamates environmental prudence with economic insights(Smith et al., 2022).

Given the wide variety of economic and environmental indicators available, each with unique measurement units, developing composite sustainability indices has proven to be complicated. Weighting models are used to lower the size of these variables in order to simplify calculations (Cerutti et al., 2013; Nuri C. Onat et al., 2019). The weights given to the various indicators have a role in the models' output. Due to their independence from subjective weights, linear programming approaches like Principal Component Analysis and Data Envelopment Analysis might serve as viable substitutes (Y. S. Park et al., 2015). The Data Envelopment Analysis technique may be used to assess the environmental effect of a system for data from several sources and is capable of handling data that are erroneous, modal, or outliers (Zhu et al., 2007). Moreover, DEA has been frequently used to evaluate the supply chain's effectiveness and assess the operating capacity, such as the container ports (J. Park et al., 2022). The DEA method is used in the applications of analyzing the efficiency of intermodal terminals and airline efficiency evaluations (Miškić et al., 2022). The infusion of PCA into the DEA model accentuates its discriminatory prowess, as demonstrated in logistics and infrastructure projects (Deng et al., 2020; Layeb et al., 2020).

In this study, we apply a recently developed model to assess the effectiveness of buses that run on alternative fuels. LCA, LCC, PCA, and DEA are all included into the model. Combining the aforementioned techniques does rid of the issues and drawbacks with the efficiency evaluation models that have been used up to this point. The application of the DEA model determines which Decision Making Units (DMUs) are effective and which are inefficient (Kucukvar et al., 2021b). However, the PCA model, which creates new primary components that are linear combinations of original variables, has been implemented in order to enhance the discriminating potential of this model (Miškić et al., 2022). The main purpose of using the PCA model is to reduce the number of variables that are linearly connected among themselves into a smaller number of new variables with little information loss(Nuri C. Onat et al., 2019). The effects of electric automobiles over their life cycles have been the subject of much research. These approaches typically examine one aspect of sustainability at a time, rather than merging the economic and environmental aspects of sustainability into a single metric, such as the eco-efficiency or sustainability performance index. Despite life cycle assessment's status as a systematic approach to complete environmental impact analysis, there is presently lack of literature providing an in-depth examination of the environmental impacts related to the energy composition of bus fleets. The authors feel that the primary conclusions coming from this study will have significance for the whole transition of public transport towards a sustainable future, and not only in the local context. A innovative method is to combine the PCA-DEA model with LCA in order to address associated environmental variables and derive composite eco-efficiency metrics. This technique considers both environmental effects and economic value added.

## 3. Methods

The paper analyzes the efficiency of alternative fuel buses used in the public transportation system in Qatar by integrating the life cycle assessment with both the principal component analysis and data envelopment analysis techniques to assess the environmental performance of six different city bus brands. A detailed research methodology is shown in Figure 1.

### 3.1 Life Cycle Assessment (LCA)

A LCA is crucial for comprehending the far-reaching sustainability implications of employing various fuel types in alternative bus models within international supply chains. Our research introduces a novel hybrid LCA model rooted in input-output analysis to comprehensively compare the sustainability impacts associated with six distinct city bus types, all within a unified framework. This study delves into exploring and comparing three alternative bus fuels: diesel buses, compressed natural gas buses, and electric buses. To facilitate the comparison among these three fuel options, we employ a set of seven environmental indicators, namely photochemical ozone generation (POF), particulate matter creation (PMF), global warming potential (GWP), land usage, human health, water withdrawal, and water consumption.

Our analysis defines system boundaries that encompass the whole life cycle of the six city buses, encompassing the impacts associated with their manufacturing, operational use, and end-of-life phases. In detail, the manufacturing phase considers the production of components such as batteries for electric buses CNG tanks, as well as the logistics and importation of buses to Qatar. These city buses originate from various countries, with two CNG buses imported from Turkey and China, two electric bus types from China and Germany, and two diesel buses from China, and Turkey. These buses all adhere to standardized parameters of 12 meters in length, 146,000 kilometers of annual mileage, and a 10-year expected service life. Furthermore, all sustainability results are expressed in kilograms per kilometer of bus travel, with 1 kilometer as the functional unit for this research. In addition to the manufacturing phase, our analysis extends to the operational phase, incorporating factors like the installation of charging stations for electric buses, bus maintenance, and repair, as well as fuel production and electricity generation. The LCA analysis pertaining to electricity generation encompasses two primary scenarios: one where the electricity source is natural gas and the other where it derives from solar energy.

Furthermore, our assessment includes the consideration of tailpipe and upstream emissions within the operating phase, collectively denoted to as Well to Wheels (WTW) analysis. The WTW study consists of two separate phases: well-to-tank (WTT) and tank-to-wheels (TTW). The WTT phase consists of three main components: local fuel supply within Qatar, the "within Qatar sectors" representing local fuel production providers, and the "outside Qatar sectors" accounting for foreign fuel production suppliers. The TTW phase explicitly addresses the direct impact of tailpipe emissions from bus fuel combustion during the operating period. Lastly, our end-of-life analysis quantifies the potential reduction in total environmental impacts achievable through recycling all evaluated bus alternatives and the

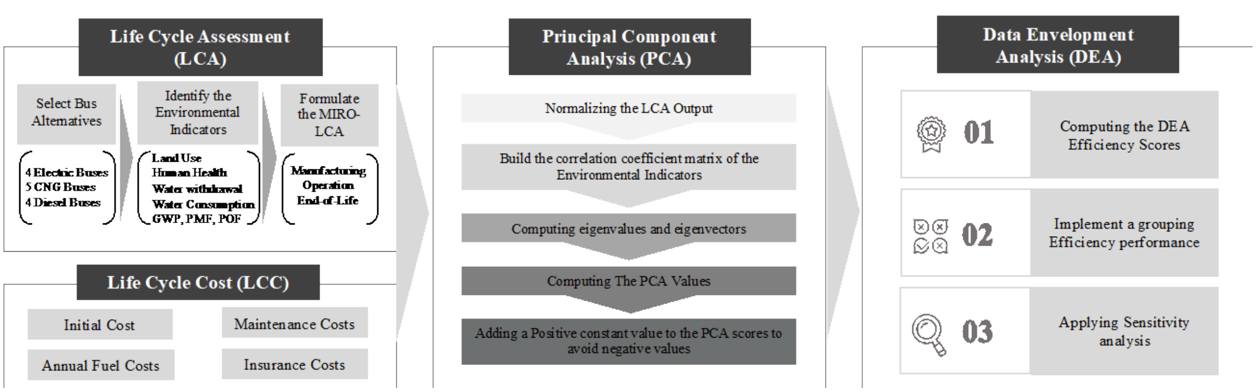


Figure 1. Applied methodology

benefits accrued from recovering components. This phase evaluates the recycling of city buses in two additional countries, China and India, thereby expanding the scope of our analysis.

### 3.2 Life Cycle Cost

The LCC analysis serves as a valuable tool for assessing and comparing various options, shedding light on their associated costs, and ultimately identifying the most cost-effective alternative over the course of its entire lifecycle. This comprehensive study dissects LCC into four fundamental components: initial expenditures, annual fuel costs, maintenance outlays, and insurance expenses. However, it is worth noting that Electric Buses (EBs) introduce additional expenses, such as infrastructure and battery replacement costs. The LCC calculations are primarily anchored in the following assumptions: an annual mileage of 150,000 kilometers traveled by each bus and an average usable lifespan of 10 years. Complete insurance coverage is factored in at 4% of the original bus price, and a salvage value equivalent to 25% of the initial bus price is considered while taking into account interest and inflation rates of 4.78% and 2.93%, respectively, as per Trading Economics data from 2021. The initial step in calculating the LCC for each bus option involves determining the present value of each cost component. Subsequently, all these cost elements are summed for each year of the bus's operational life. In this study, LCC serves as a pivotal financial analysis technique, enabling us to discern which alternative boasts the lowest overall lifecycle costs.

### 3.3 Principal Component Analysis

Indeed, the primary objective of employing the PCA model is to condense and scrutinize the linear relationships among a multitude of interrelated variables, reducing them into a smaller set of novel variables while minimizing the loss of critical information. This reduction and simplification aid in gaining a more manageable and insightful perspective on the underlying data, facilitating more effective analysis and decision-making (Miškić et al., 2022). This methodology involves transforming a set of variables into new, uncorrelated components known as Principal Components (PCs). These PCs isolate the most salient details and variation in the data. Eq. (1) provides a mathematical representation of the PCA framework (James et al., 2021):

$$
\begin{aligned}
Z_1 &= a_1^t = a_{11}x_1 + a_{12}x_2 + \cdots a_{1n}x_n \\
Z_2 &= a_2^t = a_{21}x_1 + a_{22}x_2 + \cdots a_{2n}x_n \\
&\;\;.. \\
&\;\;.. \\
Z_p &= a_p^t = a_{p1}x_1 + a_{p2}x_2 + \cdots a_{pn}x_n
\end{aligned}
\qquad \text{Eq. (1)}
$$

Where $Z_1$ ; $Z_2$ ; …; $Z_p$ are the PCs, and $a_{ij}$represents the coefficient $of\ x_j$ in ith. For each coefficient $a_{ij}$, we get the square root of the associated eigenvalue using the eigenvector. Each principal component is a linear combination of the original variables, designed to maximize information coverage with the highest variance, and each component is orthogonal to the ones that precede it.

3.3.1 Data Normalization:

The data obtained from the Life Cycle Assessment technique is structured as a matrix, with alternative buses as rows and the seven environmental indicators and LCC output as columns. To account for different measurement units, a min-max normalization technique is applied. This normalization enhances the accuracy of the subsequent PCA results.

3.3.2 Calculating the correlation matrix for the chosen indicators:

The correlation matrix of the seven environmental indicators is calculated using Eq. (2). Indicators that have correlation values of 1 or -1 demonstrate significant correlations.

$$r_{ij} = \frac{1}{n-1} \sum_{s=1}^{n} X_{si}\, X_{sj} \qquad \text{Eq.(2)}$$

Where $r_{ij}$represents the correlation coefficient between indicators $i$ and $j$, $X_{si}$ and $X_{sj}$ denote the values of indicators $i$ and $j$ in state $s$.

3.3.3 Finding Eigenvalues & Eigenvectors:

The number of components in the PCA may be determined by calculating the eigenvalues and eigenvectors, as illustrated in Eq. (3) and Eq. (4), accordingly.

$$|R - \lambda I| = 0 \qquad \text{Eq.(3)}$$

The correlation matrix of indicators is $R$ , $I$ is the unit matrix, and $\lambda$ denotes the eigenvalues. The number of PCs is equal to the number of eigenvalues found by solving Eq. (3).

$$\left(R - \lambda_j I\right) F_j = 0 \qquad \text{Eq.(4)}$$

The eigenvalue of component $j$ is denoted as $\lambda_j$, and its associated eigenvector is denoted as $F_j$ (Soler Rovira et al., 2009).

3.3.4 Determining Number of Components:

Components with eigenvalues greater than or equal to 1 are considered to capture a substantial amount of variability in the dataset and are retained for PCA calculations. Those with eigenvalues below 1 are discarded since they do not significantly contribute to the dataset's variability. If only the first component has an eigenvalue of 1 or greater, it becomes the principal component; otherwise, the principal component is a linear combination of those $Zj$ for in which the sum or product of their eigenvalues is larger or equal to one.

3.3.5 Calculating the PCA Values:

Once components are computed, PCA values for each state are determined using Eq. (5):

$$PCA\ value = \frac{\lambda_1 Z_1 + \lambda_2 Z_2 + \cdots + \lambda_j Z_p}{\lambda_1 + \lambda_2 + \cdots + \lambda_p} \qquad \text{Eq. (5)}$$

3.3.6 Adding a Positive Offset to PCA Values to Ensure Non-Negativity:

To prevent negative values, a positive constant ε is added to each PCA value, as shown in Eq. (6):

$$CEI_i = PC_i + \varepsilon \qquad \text{Eq. (6)}$$

Where $CEI_i$ represents the composite environmental impact score for state *i*, $PC_i$ is the PCA value for state $i$ and ε is a positive constant exceeding the smallest negative PCA value. It is common to see the PCA model utilized in conjunction with the DEA model in the literature. This integration serves to enhance the discriminatory capabilities of the DEA model. By leveraging PCA, a larger set of original variables is transformed into a more concise set of new variables, which effectively encapsulate their linear combinations. This consolidation of variables not only simplifies the analysis but also strengthens the separating ability of the DEA model, making it more robust and insightful in evaluating efficiency and performance across various contexts.

## 3.4 Data Envelopment Analysis

3.4.1 Efficiency Assessment

Efficiency assessment involves the use of various DEA models, each with its unique advantages and disadvantages tailored to specific research contexts(Cook et al., 2009). Among the commonly employed DEA models, the CCR (Charnes, Cooper, and Rhodes) and BCC (Banker, Charnes, and Cooper) models are well-established (Zhang et al., 2020). The CCR model, a non-oriented model, is suitable when it is assumed that DMUs generate a fixed return proportional to their size (Kucukvar et al., 2021a). In contrast, the BCC model is selected when the evaluation of DMUs' technical effectiveness is needed, considering variable returns with size. When comparing DEA models, the CCR model was chosen because it provides the most accurate efficiency measurement and the most practical outcomes (Lombardi et al., 2019). To initiate efficiency assessment, the input and output variables $x_i$ and $y_i$ of each DMU are defined. Model input (M-IP) and model output (M-OP) are then computed as in Eq. (7) and Eq.(8)to obtain a preliminary understanding of DMU efficiency (Kucukvar et al., 2021a; Nuri C. Onat et al., 2017; Nuri Cihat Onat et al., 2017):

$$M - IP = \sum_{i=1}^{N} u_i x_i \qquad \text{Eq.(7)}$$

$$M - OP = \sum_{j=1}^{z} v_j y_j \qquad \text{Eq.(8)}$$

Where N represents the total number of DMU inputs, Z is the total number of DMU outputs, $u_i$ denotes the weight associated with the $i^{th}$ input, and $v_j$ signifies the weight associated with the $j^{th}$ output. The ratio of a DMU's virtual outputs to its virtual inputs serves as a proxy for its eco-efficiency:

$$\text{Efficiency} = \varepsilon = \frac{M-OP}{VI} = \frac{\sum_{j=1}^{z} v_j y_j}{\sum_{i=1}^{N} u_i x_i} \qquad \text{Eq.(9)}$$

Mathematical programming is subsequently employed to explicitly assign weights $u_i$ and $v_j$ to each DMU. In this paper, the DEA model is denoted as following Eq. (10)-(12):

Objective Function $Max. \varepsilon = \frac{\sum_{j=1}^{z} u_j y_{jk}}{\sum_{i=1}^{N} v_i x_{ik}}$ Eq.(10)

Subject to

$$\frac{\sum_{j=1}^{z} u_j y_{jk}}{\sum_{i=1}^{N} v_i x_{ik}} \leq 1, k = 1,2, \dots\ n, \qquad \text{Eq.(11)}$$

$$u_j \geq 0, v_i \geq 0, i = 1,2, \dots Z; j = 1,2, \dots N \qquad \text{Eq.(12)}$$

$x_{ik}$ and $y_{jk}$ denote the inputs and outputs of the $k^{th}$ DMU, and $n$ is the total number of DMUs.

The careful selection of suitable performance measures, including both M-IP and M-OP, is of paramount importance in the context of the DEA optimization model, as outlined in Equations (10)–(12). This DEA model has been formulated to elucidate the influence of M-IP variables on the efficiency metrics of each bus, as detailed in Table 1.

Table 1. M-IP and M-OP of the DEA model

| Model Input | Model Output |
|---|---|
| Land Use | |
| Human Health | |
| Water Withdrawal | |
| Water Consumption | Life Cycle Cost (LCC) |
| Global Warming Potential | |
| Particulate matter formation | |
| Photochemical ozone formation | |

### 3.4.2 Efficiency Performance Grouping
Efficiency performance grouping is based on the unsupervised learning method known as K-means clustering, which groups data points according to how similar they are. The technique partitions data points into a predefined number of clusters, considering their spatial and/or attribute proximity. K-means clustering has applications in various domains such as market segmentation, customer profiling, and disease diagnosis(MacQueen, 1967). Table (2) represent the outline of the K-means clustering process (Likas et al., 2003):

Table 2. K-means clustering steps.

| Steps | Process | Details |
|---|---|---|
| 1 | Determine the Clusters (K) number | Select the appropriate number of clusters (K) for the analysis. This can be achieved by evaluating the cost function using cluster centroids. |
| 2 | Randomly Assign Data Points to Clusters | Randomly assign each data point to an initial cluster. Each data point becomes part of one of these initial clusters. |
| 3 | Calculate Cluster Centroids | Compute the cluster centroids, which represent the average of all points within a cluster in all dimensions. These centroids serve as the center of each cluster. |
| 4 | Calculate Distance from Centroid for Each Data Point | Find the Euclidean distance from each data point to the cluster's center. |
| 5 | Reassign Data Points to Clusters | Move observations closer to the cluster whose centroid is nearest, as measured by Euclidean distance. |
| 6 | Recalculate Cluster Centroids | After data points are reassigned, recalculate the centroids for each cluster. |
| 7 | Repeat Steps 4 to 6 Until Convergence | Iteratively repeat Steps 4 to 6 until centroids no longer change. This convergence indicates the completion of the clustering process. |

Upon evaluating the eco-efficiency of every sector, we performed a sensitivity analysis to gauge the degree of change in the eco-efficiency rating due to alterations in particular DEA input variables. For this analysis, we employed (Zhu, 2001) super-efficiency sensitivity model. This method concurrently considers data fluctuations for all DMUs (both the alteration of the test DMU and modifications of the other DMUs) to ascertain the relative influence of each input variable on the efficiency score.

## 5. Results and Discussion
### 4.1 LCA Results
Figure (2-8) represents the results of a Life Cycle Assessment for the six different city buses recycled in two different countries: China and India. The assessment focuses on seven environmental indicators, which are essential for evaluating the environmental impact of these buses throughout their life cycle. Starting with the Global Warming Potential impacts, electric buses from China and Germany have the lowest GWP when recycled in China or India, indicating a smaller carbon footprint. Moreover, the CNG buses from China and Turkey have similar GWP, slightly higher than electric buses. Lastly, diesel buses, irrespective of whether they are from China or Turkey, have the highest GWP. However, for the Particulate Matter Formation, Electric buses from China have the highest PMF, while Diesel buses from China and the German Electric bus have the second-highest PMF. CNG buses from China and Turkey tend to have lower PMF values than electric and diesel buses. The Photochemical Ozone Formation, commonly referred to as smog formation, results from emissions that contribute to the production of ground-level ozone, a major component of smog. This can harm human health and damage crops and other vegetation. From the provided chart, both the Electric buses from China and Germany recycled in either country have similar POF values, around 1.6E-03.

This suggests that the recycling processes for electric buses, regardless of their origin and recycling location, produce nearly equal emissions that contribute to smog. Diesel buses from China or Turkey have slightly lower POF values than Electric buses. This indicates that Diesel buses, when recycled, might contribute slightly less to the formation of photochemical ozone than Electric buses. Same as the PMF, the CNG buses from China and Turkey have the lowest POF values compared to electric and diesel buses.

Water-related impacts for the electric buses from Germany and China are the highest for both water consumption and water withdrawal indicators. Diesel buses came in second place from Turkey and China, then CNG buses. For water withdrawal, CNG buses from Turkey recycled in India have the lowest value by a significant margin. CNG buses generally tend to have lower water withdrawal values than electric and diesel buses, especially when recycled in India. Similar to water-related impacts, land use impacts tend to have the same results, with electrical buses as the highest land users and the CNG buses as the minor users. In terms of human health, electric buses from China recycled in both countries have nearly the same value, with 5.9E-10 when recycled in China and 6.0E-10 when recycled in India. The same for electric buses from Germany also have close values for both recycling locations, with 4.1E-10 in China and 4.2E-10 in India. These values suggest that the recycling processes of electric buses, regardless of origin and location, have minimal variations in human health impacts. Furthermore, Electric buses from Germany seem to have slightly lesser human health impacts compared to those from China. The human health impacts of the diesel buses from both China and Turkey have slightly higher values than the electrical buses from Germany. The impacts from CNG buses lie between electric and diesel buses. CNG buses from Turkey, when recycled, seem to have the lowest human health impacts over the six evaluated buses. From an environmental perspective, CNG buses, irrespective of their origin (China or Turkey), tend to have lower impacts on most indicators when compared to diesel or electric buses. Also, there does not appear to be a dramatic difference in environmental impacts based on the evaluated buses' recycling location (China or India). The buses recycled in India generally have very similar environmental indicators to their counterparts recycled in China.

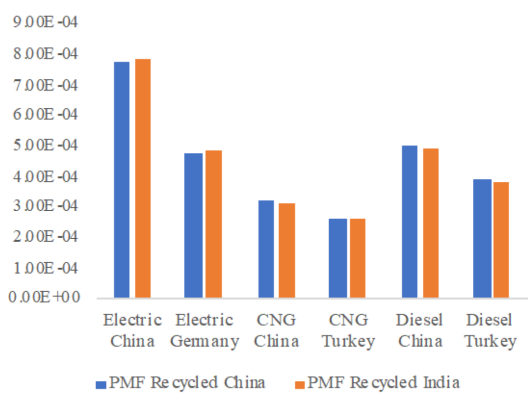


Figure 1. Particulate Matter Formation

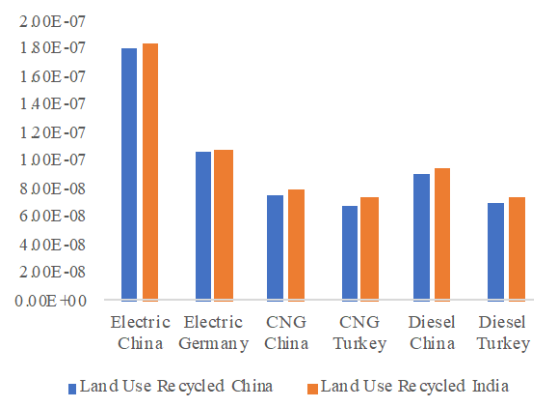


Figure 2. Land use

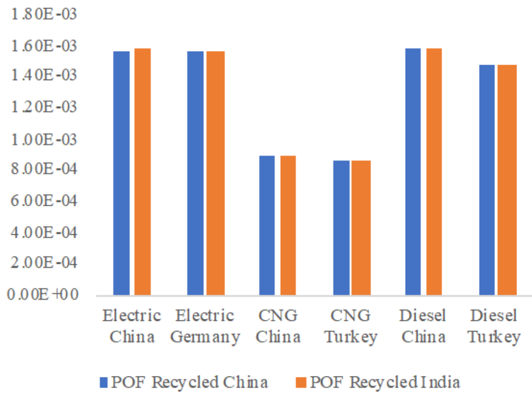


Figure 3. Photochemical Ozone Formation

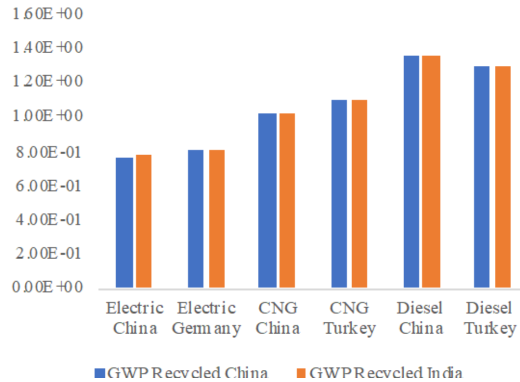


Figure 4. Global Warming Potential impacts

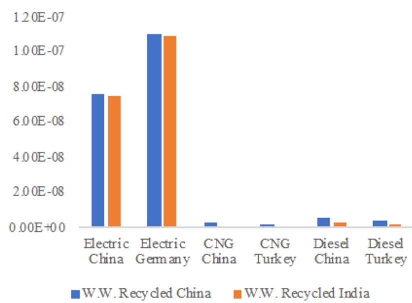


Figure 5. Water Withdrawal

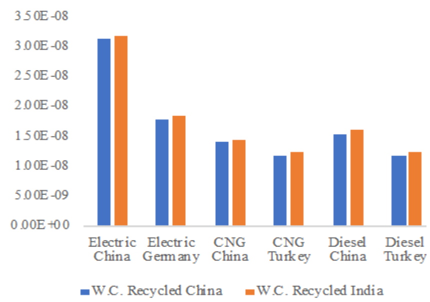


Figure 6. Water Consumption

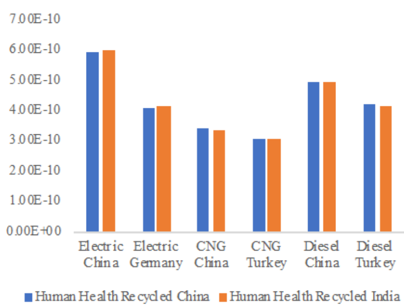


Figure 7. Human Health

## 4.2 LCC

Figure 9 presents the Life Cycle Cost (LCC) for buses powered by different fuels: Electric, Compressed Natural Gas (CNG), and Diesel. These buses are also differentiated by their countries of origin, specifically China, Germany, and Turkey. Staring with the electric buses, there's a significant price differential between the LCCs of electric buses depending on their country of manufacture. German electric buses have a higher LCC of approximately $488,475.44 compared to their Chinese counterparts. For the CNG buses the Chinese bus presents a lower LCC than the Turkish CNG bus by about $182,267.86. On the other hand, diesel buses exhibit the highest LCCs among all the categories. The difference in LCC between Chinese and Turkish diesel buses is minor, with Turkish buses being slightly more expensive by approximately $13,064.02. Overall, of the options provided, the Chinese CNG bus has the lowest life cycle cost, potentially making it the most economical choice over its lifespan. Conversely, diesel buses, irrespective of their origin, possess the highest LCCs, rendering them the least economical over their life cycle.

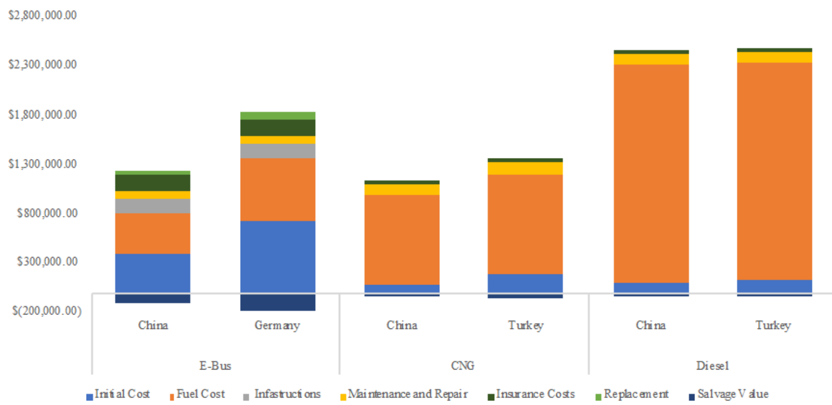


Figure 9. The Life Cycle Cost

### 4.3 PCA- DEA Results

Initially, we need to assess the efficiency of twelve decision-making units using the PCA-DEA model, meaning we must pinpoint either efficient or inefficient business years during the examined span. DEA assesses the relative efficiency of a consistent group of DMUs with multiple input and output measures. The PCA model was integrated to bolster the discriminatory capability of the DEA approach; that is, through PCA, the initial parameter count is condensed to fewer parameters that encapsulate a significant portion of information from the initial set. The gathered data for the eight pre-determined input-output parameters form the foundation for efficiency computation or the combined PCA-DEA-LCA model application. The PCA method was diligently applied to the previously defined input and output parameters set. This was done to derive the PCs, which serve as a compact representation of the original data. Following this, a detailed analysis was conducted on twelve distinct city buses. This thorough evaluation was executed using the renowned Excel add-on tool – XLSTAT.

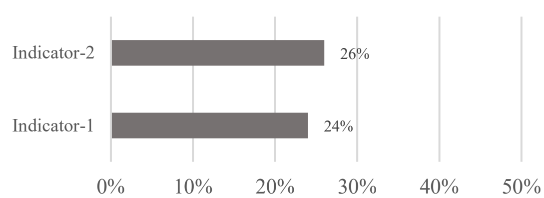


Figure 10. Sensitivity of environmental impact

By adeptly employing the PCA technique, we distilled the information from the original set of seven input parameters down to two primary components. This streamlined representation was invaluable in making sense of the data's underlying patterns. However, when it came to the output parameters, this set consisted of only a single parameter; there was no need, nor was it feasible, to reduce it further. To determine the efficiency values of the DMUs, the DEA (CCR) model was adopted. This model was crucial for our analysis, particularly in its input-oriented configuration. The conclusive results derived from the PCA-DEA technique are displayed in Table 3. Out of all the analyzed city buses, only two, specifically DMU3 and DMU9 (Chinese CNG recycled in China and India), managed to achieve the pinnacle of efficiency; this indicates a remarkable performance by these two units compared to their counterparts.

Table 3. PCA-DEA model Results

| DMU | Recycling | China | | | | | | India | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Type | Electric | | CNG | | Diesel | | Electric | | CNG | | Diesel | |
| | Manufacturer | $China_1$ | $Germany_2$ | $China_3$ | $Turkey_4$ | $China_5$ | $Turkey_6$ | $China_7$ | $Germany_8$ | $China_9$ | $Turkey_{10}$ | $China_{11}$ | $Turkey_{12}$ |
| **Score** | | 0.0929 | 0.0885 | 1 | 0.4144 | 0.1232 | 0.1334 | 0.0918 | 0.0877 | 1 | 0.3773 | 0.1214 | 0.1313 |

The efficiency performance grouping focuses on categorizing the DMUs based on their efficiency outcomes. A prominent technique suitable for this task is k-means clustering. This strategy aims to divide n data points into k clusters where each data point associates with the cluster having the closest mean. In our research, these clusters have been labeled as "Poor," "Fair," and "Excellent." Such categorization offers insights into the effects of incorporating the outputs on the efficiency performance evaluation. Once the boundaries for these categories are established, each DMU is allocated to a group based on its $\varepsilon$ value. Table 4 presents the color-coded group assignments for our DEA model explored in this research. The uniformity in color coding signifies the stable efficiency performance across the twelve city buses in our eco-efficiency model. Findings reveal that CNG buses consistently achieved an "Excellent" rating across all examined recycling scenarios. On the contrary, electric buses exhibited a "Poor" rating, maintaining this trend across both recycling countries. However, the diesel buses demonstrated a moderate "Fair" performance, influenced by the variations in the recycling country.

The sensitivity of each environmental impact category influences the eco-efficiency of various city buses. Results from the sensitivity analysis revealed that average sensitivity ratios fluctuated between 24% and 26% (as seen in Figure 10). Typically, environmental impact categories with a heightened sensitivity ratio necessitate smaller percentage enhancements to achieve complete efficiency.

Table 4. Efficiency Performance Grouping

| **Buses** | | | **Environmental Model** |
|---|---|---|---|
| Recycling | Type | Manufacturer | |
| China | Electric | China | **3** |
| | Electric | Germany | **3** |
| | CNG | China | **1** |
| | CNG | Turkey | **1** |
| | Diesel | China | **2** |
| | Diesel | Turkey | **2** |
| India | Electric | China | **3** |
| | Electric | Germany | **3** |
| | CNG | China | **1** |
| | CNG | Turkey | **1** |
| | Diesel | China | **2** |
| | Diesel | Turkey | **2** |

Color Code Key:

| 1 | Excellent | 2 | Fair | 3 | Poor |
|---|---|---|---|---|---|

## 5. Conclusion

The extensive examination of various city buses, across different environmental indicators and life cycle costs, provides illuminating insights into their eco-efficiency and economic viability. The life cycle assessment underscored the environmental performance of buses based on their type and the country of recycling, revealing that CNG buses generally had lower impacts across most indicators than their diesel or electric counterparts. Surprisingly, the location of recycling—whether in China or India—did not drastically alter these environmental footprints. Meanwhile, the life cycle cost analysis highlighted a marked difference in cost-efficiencies based on bus type and country of origin. Diesel buses, despite their popularity in many regions, exhibited the highest life cycle costs, making them less economical in the long run. On the contrary, the Chinese CNG bus stood out as a potentially more affordable and environmentally friendly alternative over its lifespan. Furthermore, the PCA-DEA analysis affirmed the superior efficiency of the Chinese CNG buses recycled in China and India, reinforcing the potential benefits of CNG buses. The k-means clustering further categorized the buses into performance tiers, with CNG buses consistently ranking high. Finally, the sensitivity analysis, emphasizing the environmental impact categories, indicated that even minor improvements in high-sensitivity areas could lead to significant strides in eco-efficiency. In synthesis, for cities aiming for a sustainable transport model that combines both ecological and economic benefits, CNG buses, particularly those originating from China, emerge as a compelling choice. Decision-makers would do well to consider these findings when planning future urban transportation strategies. As a future work, the author is planning to extend LCA into life cycle sustainability assessment (LCSA) to incorporate a more exhaustive list of environmental, economic, and social indicators to provide a holistic understanding of the life cycle impacts of alternative bus types.

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