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Integrating Life Cycle Sustainability Assessment and Multi-Criteria Decision-Making for Sustainable Transit Bus Fleet Optimization

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Abstract

This research aims to enhance the existing methods for assessing the sustainability of various transit buses. It integrates life cycle sustainability assessment (LCSA) with multi-criteria decision-making. Thirteen bus brands are evaluated for their macro-level sustainability impacts. Two scenarios for bus end-of-life (EoL) are considered: recycling in China and India. The study assesses all bus types' environmental, social, and economic impacts, identifying optimal distributions for each scenario. A compromise programming model is developed to determine the best mix of alternative vehicles, considering the importance of different sustainability indicators and study scope. The study also explores the total impacts of global supply chains on these distributions. Findings indicate that Compressed natural gas (CNG) buses recycled in India are most favorable. With environmental indicators prioritized, the ideal mix is mostly Swedish CNG, with a small percentage of Indian CNG, both recycled in India. However, if economic indicators are prioritized, Indian CNG buses recycled in China dominate the fleet. For social indicators, Turkish CNG recycled in India comprises the majority. In a balanced scenario, Swedish CNG recycled in India forms over 95% of the distribution.

Keywords
Life cycle sustainability assessment, Alternative Transit buses, multi-criteria decision making.

1. Introduction

Transport and the environment are dynamically intertwined in a contradictory way. While there are undoubtedly positive social and economic effects, public transportation also negatively impacts the environment. Carbon emissions as a percentage of total emissions have risen since both population and economic expansion have led to a sharp rise in the proportion of people who utilize transportation services (Fernández-Amador et al., n.d.). The transportation industry releases millions of greenhouse gases (GHGs) annually, accounting for around 25%-30% of the global total (IEA, 2018). Compared to the average yearly rise of 1.9% seen since 2000, total transportation emissions have fallen below 0.5% in 2019. Still, international transportation accounts for 21% of 2018's total CO_2 emissions, as reported by the International Energy Agency (IEA) (IEA, 2018). Regarding transportation, road vehicles account for more than 74% of CO_2 emissions or 15% of overall CO_2 emissions (International Organization of Motor Manufacturers, n.d.). Many social, economic, and environmental benefits should accrue from adopting a sustainable transportation system, which in turn helps to advance sustainable development objectives. Developed nations all over the globe are working hard to find a solution to the problem of sustainable development's inherent tension with environmental degradation. Modern technology and alternative fuels are being incorporated progressively into transportation fleets as part of a worldwide drive toward a more environmentally friendly transportation system. Eliminating reliance on finite fossil fuel supplies requires widespread adoption of renewable energy sources, including biofuels, electricity, hydrogen, and CNG (Pamucar et al., 2021). The power-generating mix is also essential since it is directly connected to the CO_2 intensity of the energy used to charge electric vehicles and plug-in hybrid electric vehicles. The intensity of CO_2 emissions is also affected by the country's power-generating mix. Thus, the optimal choice for brand-new automobiles differs from one nation to another. However, deciding on the ideal automobile is a complex matter with many variables. In addition, a consistent multi-criteria framework is necessary for enforcing sustainable judgments to arrive at optimum designs for road transport fleets. This study used the Life Cycle Sustainability Assessment methodology because it aims to consider the environmental, social, and economic aspects. However, determining the best vehicle distribution for a more sustainable transportation system may need more information than can be gleaned from a simple quantification of these impacts alone. In order to identify optimum solutions, multi-criteria decision-making models are best suited for addressing the competing objectives of each of the selected impacts.

1.1 Objectives

Using the case of the State of Qatar, this research examines the environmental, social, and economic consequences of three distinct fuel choices (electric, CNG, and diesel buses) under various recycling scenarios to find the optimal transit bus distributions. Specifically, it seeks to:

1. Enhance Life Cycle Sustainability Assessment Methodologies:
   Adapt and enhance the LCSA approach to quantify the impacts of different transit bus alternatives on the environment, society, and economy while considering the world's supply chain.
2. Integrate Multi-Criteria Decision-Making with LCSA:
   Develop a robust framework that combines Multiple-Criteria Decision-Making approaches with Life Cycle Sustainability Assessment to assess and compare the sustainability of various transit bus brands and fuel types in different end-of-life situations.
3. Optimize Transit Bus Fleet Composition:
   Utilize a compromise programming model to determine the optimal mix of transit buses that balances environmental sustainability with social and economic benefits under multiple weighting scenarios for sustainability indicators.

2. Literature Review

The literature places a lot of focus on quantifying the social and economic implications of sustainability in addition to the environmental ones, which has led to the current shift from Life Cycle Assessment (LCA) to Life Cycle Sustainability Assessment . The LCSA approach implies including sustainability's environmental, economic, and social components into traditional LCA methodologies (Ciroth et al., 2011; Sala et al., 2013). The LCSA approach takes into account a product, process, or system's whole life cycle to calculate its full economic, social, and environmental impact. Additionally, the LCSA's focus has changed from a macro-level effect assessment to a product-level impact assessment. However, there has been much focus on LCSA's potential applications to different problems, even though the industry has yet to embrace this strategy widely. From 2010 to 2020, this decade has been dubbed the "decade of life cycle sustainability analysis," and various studies have stressed the necessity for horizontal development in LCA methodology with new social and economic dimensions (Guinée et al., 2011). It was Kloepffer in 2008 (Kloepffer, 2008), who initially developed and formalized the present LCSA technique, whereby the LCSA equals the total of the three distinct methods such as : LCA, life cycle cost (LCC) assessment, and social life cycle assessment (S-LCA) (Finkbeiner et al., 2010).

While there has been little development of LCSA in terms of its methodological elements and breadth of application, a recent assessment by United Nations Environment Program (UNEP) and the Society of Environmental Toxicology and Chemistry (SETAC) suggests that this is a powerful framework that deserves further development (Nuri Cihat Onat et al., 2016). Integrating MCDM techniques into LCA studies will be crucial to bolster the LCA method as a tool and increase its utility for sustainable decision-making (Hermann et al., 2007; Jeswani et al., 2010). The literature shows that MCDM approaches have been widely used for LCA. In 2011, Boufateh and Perwuelz , for instance, analyzed the LCA outcomes of textile products using an MCDM approach (Boufateh et al., 2009). For nano-manufacturing and the management of polluted sediments, Linkov and Seager (Linkov et al., 2011) provided an MCDM strategy that combined uncertain information gathered through risk analysis and LCA. A fuzzy MCDM technique was utilized by (Kucukvar et al., 2014) to rate the life cycle sustainability performance of warm-mix and hot-mix asphalt pavements built in the United States. Many different LCA models have been created for environmental evaluations of alternative vehicle technologies, but very few studies have addressed MCDM as an integrated decision-making framework for these options(Nuri C. Onat et al., 2022). Using an optimization model, (Donateo et al., 2008) created a hybrid electric vehicles resulting from a two-stage process that included optimization and decision-making. Moreover, to find the best designs for internal combustion vehicles (ICVs), hybrid electric vehicles (HEVs), PHEVs, and EVs, (Traut et al., 2012) established a hybrid LCA model and built an optimization model, choosing the costs and GHG emissions of each vehicle type as competing objectives. However, none of these research employed multi-objective optimization models to take into account alternative transit buses' immediate and long-term implications on society, the economy, and the environment from an LCSA viewpoint. In order to determine the best transit bus distribution for the state of Qatar's public transportation fleet, taking into account the trade-offs between the relevant environmental, economic, and social dimensions of sustainability, this study will build a Compromise Programming model using the multi-objective optimization method.

3. Methods

In order to determine the best distribution of transit buses using various fuel types in the state of Qatar, the analysis in this research is based on a structure that combines the MCDM and the LCSA model. The LCSA model's computed sustainability impacts consider many environmental, social, and economic indicators, along with the corresponding weights for each indicator. The optimal distribution for the chosen transit buses is then determined using a multi-objective optimization model. The optimization findings in this study are based on the quantifiable life-cycle impact of each transit bus, with weights assigned to each impact category. Figure (1) is an illustration of the methods provided in this research.

3.1 LCSA

To understand how transit buses utilizing different fuels affect global supply chains, an LCSA is needed. This study suggested a hybrid LCSA model based on a multiregional input-output (MRIO) framework to assess different fuel transit bus brands' environmental, social, and economic impacts. We compare diesel buses (DB), CNG, and electric transit bus fuels. These three alternative fuel buses are assessed using 13 environmental, social, and economic sustainability characteristics. Six key environmental indicators are global warming potential (GWP), particulate matter formation (PMF), land usage, photochemical ozone generation (POF), water consumption, and water withdrawal. The four social indicators are health, compensation, total tax, and employment. Finally, the social component comprises GDP, operational surplus, and life cycle cost. Our research examines system-level production, operation, and recycling effects to compare transit buses' life cycles. The manufacturing impact evaluation considers CNG tanks, bus shipping to Qatar, and electric buses (EB) battery production. At successive LCSA levels, several transit bus brands and models are studied. Five Chinese, Turkish, Indian, Polish, and Swedish CNG bus manufacturers and four Chinese, Swedish, Spanish, and German EB manufacturers are imported. The study includes four more Chinese, Polish, and Turkish DBs. The research buses all had the same length (12 meters), average yearly mileage (146,000 kilometers), and service life (10 years). This research uses 1 km of bus travel as a functional unit, and sustainability impacts are measured in kg/km. This research analyzes operational impacts on energy and fuel production, bus maintenance and repair, and EB charging station infrastructure. Operation includes upstream (WTW) and tailpipe emissions. This procedure has two stages: well-to-tank (WTT) and tank-to-wheels (TWW). MRIO-LCSA divides the WTT into three parts: First, domestic fuel supply, which includes Qatari power plant-generated petroleum, CNG, and electricity. The second component, "inside Qatar sectors," covers fuel producers' impacts but not fuel supplies. Third, foreign industries, such as gasoline providers, influence it. In contrast, the TTW shows bus fuel combustion tailpipe emissions during operation. Finally, the end-of-life phase considers how recycling all transit buses evaluated in this study may reduce total impacts. The end-of-life phase examines recycling in China and India, expanding the study's scenarios to twenty-six outcomes. Equations for the MRIO-LCSA model.

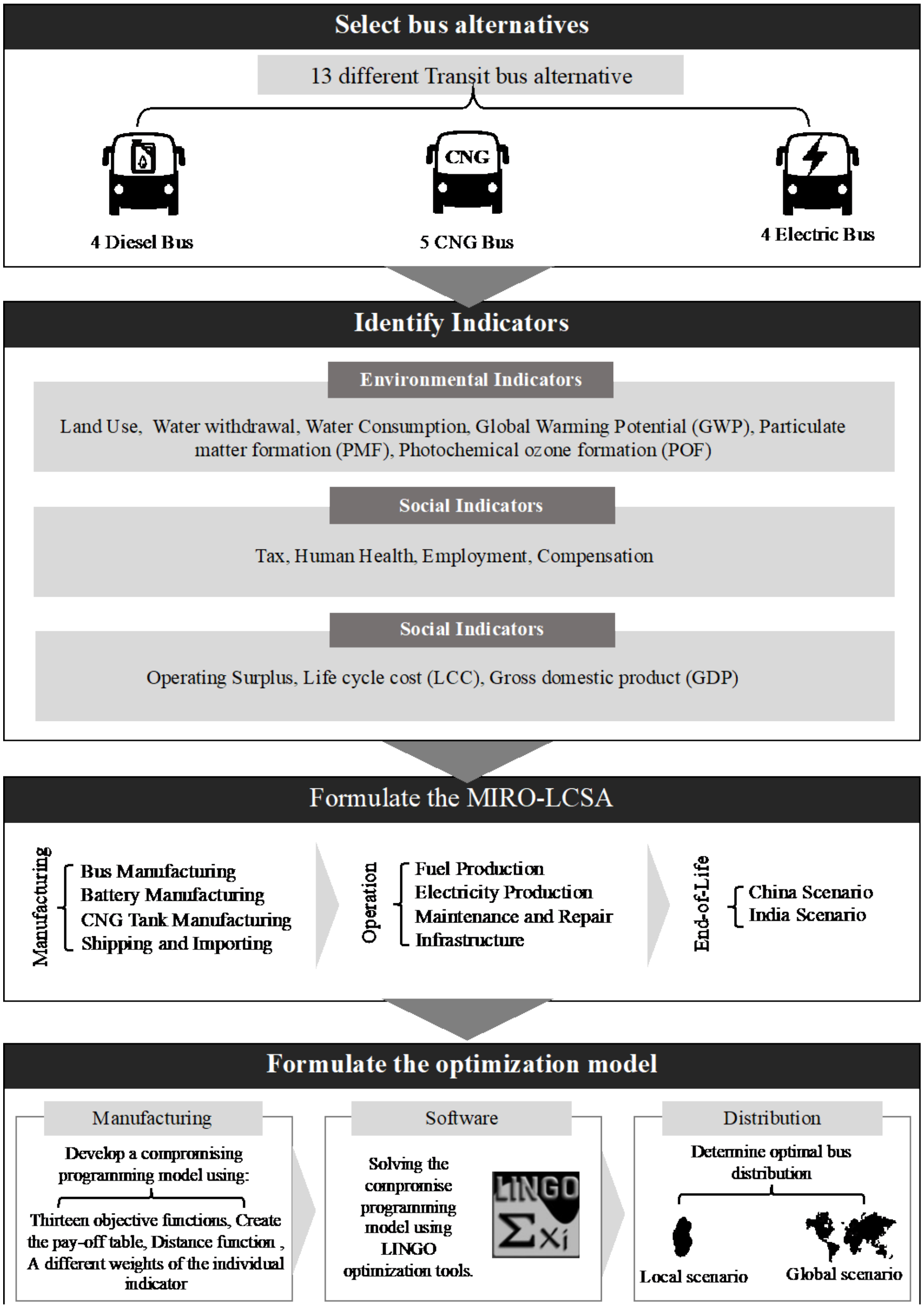


Figure 1. Research Methodology.

3.2 Multi-objective optimization model

The conflicting objectives are identified in accordance with the quantification of the sustainability indicators. Employment, operation surplus, GDP, compensation, and government tax favorably influence social and economic categories and should be maximized. All other environmental, economic, and social indices have negative implications. The Multi-Objective Decision Making (MODM), one of the basic MCDM techniques, is required to determine the ideal distribution of transit bus brands to maximize all goals. A compromise programming model is established to solve multi-objective linear, nonlinear, or integer programming problems. Zelany (1973) was the first to propose the Compromise Programming technique, which seeks to discover a solution set closest to the ideal solution point in terms of some distance measure (Zelany, 1973). Finding solutions entails assessing a subset of non-dominated solutions using a distance-based function that gauges how near these points are to the ideal solution. Eq. (1) depicts the distance-based function based on Minkowski's L_a metric (Chang et al., 2011). The L_a metric denotes the distance between two points, Z_k^* and $Z_k(x)$, as:

$$L_a = \{\sum_{k=1}^{P} \pi_k^a \, (Z_k^*(X) - Z_k(X))^a\}^{\frac{1}{a}} \tag{1}$$

"a" is the distance parameter that ranges between 1 and ∞ ($1 \leq a \leq \infty$). The weight corresponding to each objective is represented by parameter π_k^a, while the parameter "P" represents the total number of objectives. The "Z_k^*" is the optimal solution for objective "k," and $Z_k(X)$ is a function of objective k. However, Eq. (1) cannot be used for decision analysis since those goals employ incommensurable units. Usually, rescaling is required before performing the optimization analysis. In order to eliminate the possibility of bias in the trade-off process, the values after rescaling or normalization might be kept to a defined range such as [0,1]. Therefore, the scaling function represented in Eq. (2) is used in our analysis as follows (Chang et al., 2011):

$$Z = \frac{Z_k^* - Z_k(X)}{Z_k^*} \tag{2}$$

The distance-base function after normalization can be represented as follows:

$$Min \qquad L_a = min\left\{\sum_{k=1}^{P} \pi_k^a \left(\frac{Z_k^* - Z_k(X)}{Z_k^*}\right)^a\right\}^{\frac{1}{a}} d \tag{3}$$

Subject to:

$$\pi_k \geq 0, \sum_{k=1}^{P} \pi_k \tag{4}$$

And,

$$1 \leq a \leq \infty \tag{5}$$

The model below has been presented to optimize the usage of alternative city buses based on several environmental, social, and economic considerations.

<u>Indices:</u>

t: Sustainability indicator,
u: City bus type,
s: Number of sustainability indicators,
b: Number of buses

<u>Parameters:</u>

A_{tu}: The environmental, economic, and social impacts of bus u for sustainability indicator t
W_t: The weight assigned to each sustainability indicator t

Decision variables:

X_{tu}: The percentage of a bus u that is allocated to the sustainability indication t

<u>Objective function</u>*:*

$$Min \;\; Z_t(x) = \sum_{t=1}^{s} \sum_{u=1}^{b} W_t A_{tu} X_{tu} \tag{6}$$

Subject to

$$\sum_{u=1}^{b} X_{tu} = 1 \; for \; t = 1,2,3, \ldots, s \tag{7}$$

$$X_{tu} \geq 0 \; for \; t = 1,2,3, \ldots, s \;, and \; for \; u = 1,2,3, \ldots, b \tag{8}$$

Eq. (6) denotes the environmental, economic, and social objective function, in which a total of thirteen objective functions are included. In more detail, the Zt(x) represents the environmental, economic, and social objective function, W_t illustrates the weight of each impact of the thirteen indicators we studied in this study, and the total of W_t is 1. The A_{tu} signifies the potential impacts of the environmental, economic, and social indicators for alternative bus types u. In this study, we used the total impacts provided by (Elagouz et al., n.d.) each transit bus has thirteen environmental, economic, and social impacts during the life cycle, including the manufacturing, operation, and end-of-life phase. The optimization process follows the technique in (Cihat Onat et al., 2020; Nuri Cihat Onat et al., 2016): the indicators with a negative impact are converted into minimization form by multiplying each objective function by -1. Then, minimize all the thirteen objective functions. After that, create the pay-off table by optimizing every objective function individually to develop the distance function represented in Eq. (2). This distance-based function, known as the "Euclidean distance," provides solutions that are as near to the optimal solution as feasible in terms of weighted geometric distance. Our analysis covers sixteen weighting scenarios for each indicator. The weights of each scenario are a result of multiplying the priority weight of the three dimensions of sustainability and the weight of the individual indicator obtained by the Analytic Hierarchy Process (AHP), as in Table (1) & (2). The compromise-programming approach is then integrated with the MRIO-LCSA findings to optimize the different environmental, economic, and social objective functions. The compromise programming model is then developed and solved using LINGO optimization tools.

Table 1. Priority weights scenarios

Category Weights			
Scenario No.	**Environment**	**Social**	**Economic**
1	1	0	0
2	0.75	0.25	0
3	0.5	0.5	0
4	0.25	0.75	0
5	0	1	0
6	0.75	0	0.25
7	0.5	0.25	0.25
8	0.25	0.5	0.25
9	0	0.75	0.25
10	0.5	0	0.5
11	0.25	0.25	0.5
12	0	0.5	0.5
13	0.25	0	0.75
14	0	0.25	0.75
15	0	0	1
16	0.33	0.33	0.33

Table 2. AHP Weights For Each Indicator

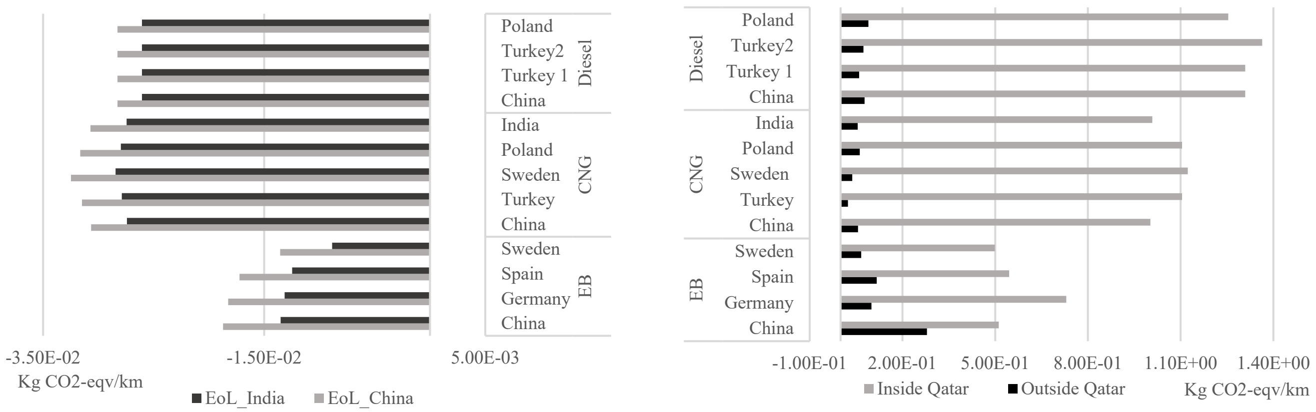
Categories	**Weights**					
Environment Indicators	**GWP**	**PMF**	**POF**	**Land Use**	**Water Consumption**	**Water Withdrawal**
	0.405134	0.199184	0.13393	0.051026	0.1377806	0.0729454
Social Indicators	**Human Health**		**Compensation**	**Employment**	**Tax**	
	0.625748		0.10547602	0.2260684	0.042708	
Economic Indicators	**Operating Surplus**		**GDP**	**LCC**		
	0.325438		0.4036732	0.30919098		

4. Results and Discussion

4.1 LCSA Result

This study categorizes Qatari and foreign LCSA results. The case is examined using the EB's infrastructure, maintenance, and repair impacts, the TTW, and the WTT, which exclusively includes Qatar's fuel supply and sectors. The outside Qatar assessment includes WTT, production, and shipment into Qatar. GWP, PMF, POF, land usage, water consumption, and withdrawal are environmentally important metrics. Overall environmental statistics reveal that EBs increased environmental impacts more than DBs and CNG buses. Land usage, PMF, water withdrawal, and consumption were most affected by EBs. Alternative buses' environmental impacts in Qatar are primarily regional. Figures (2-b) and (2-a) indicate the GWP implications inside and outside Qatar and the end-of-life benefits of recycling the thirteen-transit bus. Electric buses emit much less GWP per kilometer than fossil fuel buses. The Swedish EB has little GWP impact on 13 bus brands. The Chinese model offers larger EoL GWP gains, notably in EB. Qatar had substantially higher GWP and POF impacts than abroad. Except for the Chines E-bus, PMF affects inside Qatar were far bigger than outside. However, land use indicator effects, notably for EBs, were different. Bus and battery manufacturing required a lot of land, therefore the impact was higher outside Qatar. Global EoL analysis found that recycling EBs had fewer benefits than DB and CNG buses in China and India. The Chinese scenario outperformed the Indian scenario in environmental impacts except for water extraction.

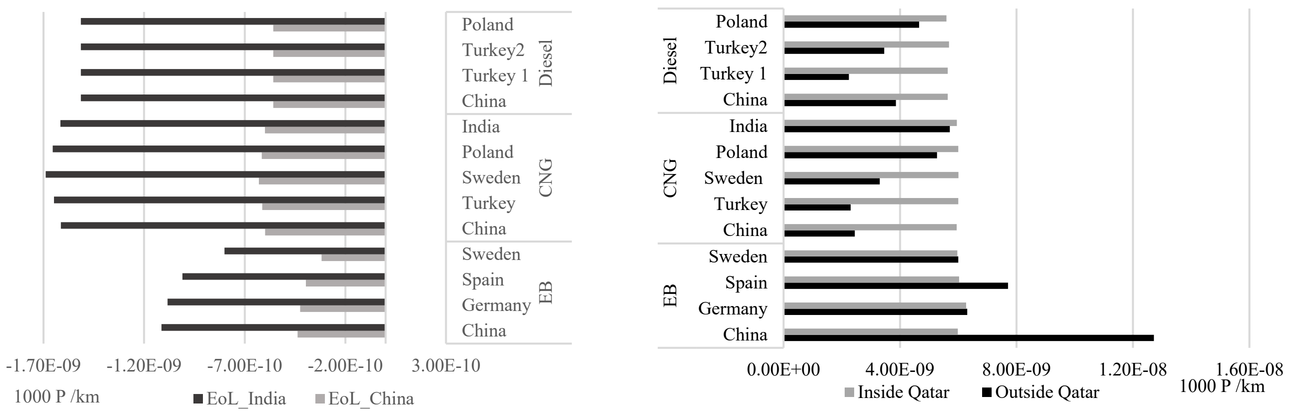
Key social indicators in our research are health, compensation, taxation, and employment. EBs have the best salaries and employment benefits compared to DBs and CNG buses due to their production and supply chain advantages. Most social impacts occur inside Qatar's regional boundaries, except for the EBs. Qatar only experienced health effects from EB, but compensation, taxation, and employment were outside Qatar. India outperformed China in EoL employment and pay because recycling DBs and CNG buses enhanced human health more. Chinese recycling raised DB and CNG bus tax benefits, but Indian recycling diminished them. Figures (3-b and 3-a) illustrate that recycling transit buses created jobs in Qatar and abroad. EBs and CNG buses had similar employment advantages in Qatar, but DBs had fewer. However, EBs had more outside employment benefits than DBs and CNG buses. Recycling created more jobs in India than China across the thirteen transit bus scenarios. In China and India, CNG transit bus recycling generates the most jobs. Statistics in this study include GDP, operating surplus, and LCC. In LCSA figures, EBs have the highest manufacturing added value of all bus brands and dominate GDP impacts. Like environmental and social impacts, ecological impacts are spatial. Economic growth was higher for EBs than DB and CNG buses outside Qatar. However, CNG buses raised nominal GDP and operational sur-plus. Figure (4-b) illustrates that the four EBs' operating surplus advantages outside Qatar are almost double those inside Qatar. DBs have the largest operational excess because to fuel supply issues. Recycling evaluated transit vehicles enhanced operating surplus by over 10% in China compared to India (Figure 4-a).



(a- End-of -life)

(b- inside/ outside Qatar)

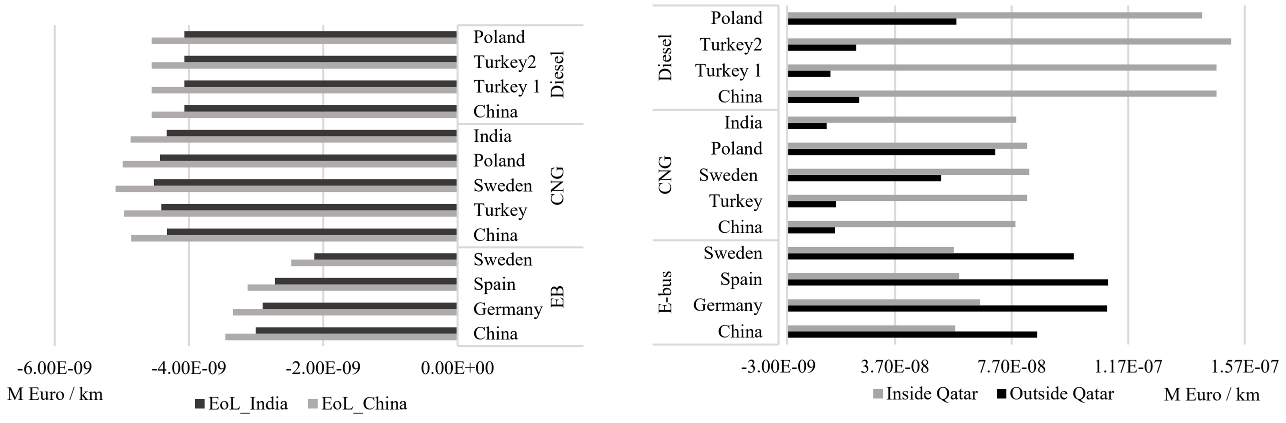
Figure 2. GWP LCSA Impacts



(a- End-of -life)

(b- inside/ outside Qatar)

Figure 3. Employment Benefits Impacts



(a- End-of -life)

(b- inside/ outside Qatar)

Figure 4. Operating Surplus Benefits

4.2 Optimal distribution of transit buses

The optimization model analysis in this study is covering the overall impacts of the buses' life cycle, including the manufacturing, operation, and end-of-life phases. The proposed optimization model considers the variability in the decision maker's priorities by allocates sixteen different sets of weights to the environmental, economic, and social impacts. All weights are scaled between 0 and 1, offering the decision-maker some flexibility by allowing them to assign weights to the different sustainability indicators depending on their different objectives. Furthermore, a compromise programming model is developed to determine the optimal distribution of the alternative buses, considering the priorities of the thirteen indicators evaluated in this study.The optimization results associated with the overall impact of the alternative buses evaluated in this study are represented in Figure (5). The optimization model is assessing the LCSA results of thirteen different buses that would be recycled either in China or India, making the total evaluated alternatives into twenty-six buses. The optimal distributions of overall alternatives, show domination for the CNG buses recycled in India. In addition, the findings are restricted to just five buses over the twenty-six buses covered in this study. The Swedish CNG recycled in India is found to have the highest distribution rate, since it is a part of the fleet distribution in eleven weight scenarios, as denoted in Figure (5). Moreover, compared to the corresponding percent fleet shares of the Swedish CNG, the Indian CNG recycled in India is selected in small percentages in eight different weight scenarios. The involvement of the Indian CNG recycled in India in the fleet shares reached 17% and 34% in scenarios 11 and 13, when the economic category had 50% and 75% of the total priority, respectively.

In more detail, when the environmental indicators had an absolute priority (i.e., priority weight is 1) in scenario 1, as presented in Figure (5), the optimal bus distribution consists of 99% Swedish CNG recycled in India and 1% the Indian CNG recycled in India. In contrast, all other bus alternatives are not selected in this scenario. However, when all the priority weight goes to the social indicators, as shown in scenario number 5 in Figure (5), the optimal bus distribution consists of 90% Turkish CNG and 10% Chines CNG both recycled in India. Compared to other social indicators, human health is prioritized with greater than 60 percent of the total weight; at the same time, the Turkish CNG has the lowest human health impacts. Due to these facts, the Turkey CNG recycled in India is selected to be part of the fleet formation in many weight scenarios with different percentages when social indicators have high priority, such as scenarios 3,4,8, and 9. Nonetheless, when the economic indicators were given complete importance over the environmental and economic indicators, the Indian CNG bus recycled in China possessed one hundred percent of the fleet distribution. Since the recycling process of the Indian CNG in China had more benefits regarding GDP than recycling the same bus in India. Moreover, the allocated weight for the economic indicators is given the GDP the highest share with 40% overall weight. Lastly, for the balanced weighting case in scenario 16, where the environmental, economic, and social indicators have equal priority weight (0.33), the optimal bus distribution consists of 95% Swedish CNG recycled in India and only 5% Indian CNG recycled in India.

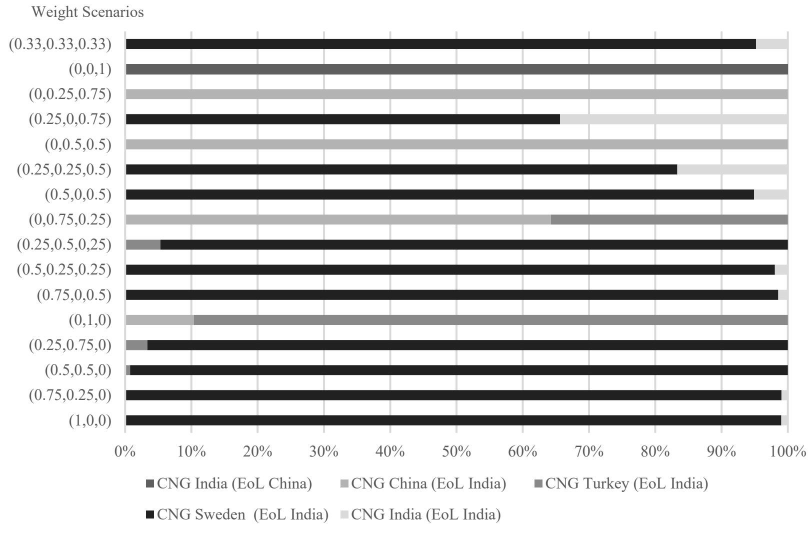


Figure 5. The Global distributions

5. Conclusion

This article demonstrated the advantages of integrating MCDM models with the LCSA framework to show how quantifiable sustainability indicators may be utilized for policy objectives; aligning with the compromise programming model could help generate optimal distribution for alternative vehicles by different environmental and socio-economic weights. Furthermore, the suggested compromise programming model's findings demonstrated that optimum solutions shift when the relative importance of environmental and socio-economic factors changes. The appropriate mix of alternative vehicles is a dynamic issue that calls for multi-stage solutions and evaluations of future circumstances. The overall findings indicate that the optimum distributions of the twenty-six options over the sixteen-weight scenarios clearly favor the CNG buses that have been recycled in India. In the scenario where environmental impacts are given supreme importance with 100% priority, the best fleet mix consists of 99% of the Sweden CNG bus recycled in India and 1% of the CNG made and recycled in India. However, when economic factors are prioritized, the Indian CNG bus, recycled in China, comprises 100% of the fleet. Despite this, when all the priority weight is put on the social parameters, the Turkish CNG recycled in India makes up more than 90% of the bus fleet. And last, in the scenario of balanced weighting, the Swedish CNG that was recycled in India accounts for more than 95% of the distribution. This research aims to provide a workable strategy incorporating hybrid LCSA and multi-objective optimization with different fixed weights to allocate the optimal transit bus distribution for Qatar. The authors also suggest separating the local impacts -that occur inside Qatar- in the optimization analysis from the Global supply chain impacts, which could give a different fleet distribution that serves the benefit of Qatar.

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