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# Environmental efficiency of electric vehicles in Europe under various electricity production mix scenarios

Murat Kucukvar<sup>a,\*</sup>, Nuri C. Onat<sup>b</sup>, Adeeb A. Kutty<sup>a</sup>, Galal M. Abdella<sup>a</sup>, Muhammet Enis Bulak<sup>c</sup>, Fajr Ansari<sup>a</sup>, Gurkan Kumbaroglu<sup>d</sup>

<sup>a</sup> Mechanical and Industrial Engineering, College of Engineering, Qatar University, Doha, Qatar

<sup>b</sup> Qatar Transportation and Traffic Safety Center, College of Engineering, Qatar University, Doha, Qatar

<sup>c</sup> Industrial Engineering, College of Engineering and Natural Sciences, Uskudar University, Istanbul, Turkey

<sup>d</sup> Industrial Engineering, Faculty of Engineering, Boğaziçi University, Istanbul, Turkey

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## ABSTRACT

Decarbonizing residential transportation sector depends on the energy mix. A need for environmental efficiency of electric vehicles considering the life cycle impacts of electricity generation under different mix scenarios is essential. This research aims to present the first empirical analysis on the environmental efficiency of battery electric vehicles across 27 European countries, considering the average electricity mix, marginal electricity mix (2015–2020), and renewable energy-based electricity mix (2030–2040) scenarios. The midpoints environmental impacts per kWh electricity generation were estimated for each country using the latest ecoinvent v3.7 life cycle environmental impact data. Well-to-wheel environmental impacts of battery electric vehicles were calculated for each country based on a functional unit per km traveled. An input-oriented non-restricted and weight restricted frontier models using the panel-based weights obtained from the European Commission's Joint Research Center (JRC) survey was built to model the environmental efficiency. Finally, the footprint efficiency results related to different electricity production mix scenarios and future projections to improve the environmental efficiency of battery electric vehicles were suggested. The results reveal Finland and Netherlands as the most environmentally efficient countries using BEVs for all the electricity mix scenarios. It is seen that average mixes cause lower environmental efficiency scores of battery electric vehicles than marginal mixes due to higher shares of renewable electricity sources in marginal mixes.

## 1. Introduction

### 1.1. Background

Road transportation of passengers and freight accounts for nearly a quarter of the global CO<sub>2</sub> emissions, one of the principal anthropogenic greenhouse gases (GHG) (EEA, 2020). For the periods between 1995 and 2019, emissions from passenger vehicle transportation have increased by 28% globally instead of a planned decrease of 2.5 metric tons of emissions from light-duty vehicles by 2020 (IEA, 2019). Electrified powertrains continue to gain popularity worldwide as a dominant clean fuel alternative to the traditional “internal combustion vehicles” (ICV) (Heidrich et al., 2017). European countries have started to show some pockets of growth in the EV uptake rate since 2014 (EEA, 2020). Europe stands as the first runner-up to date in EV adoption due to the declining

manufacturing costs and nationwide charging infrastructure deployment (IEA, 2019). The EU-wide EV sales have captured over 1.8 million vehicle registrations in the “battery electric vehicle (BEV)” and “plug-in hybrid electric vehicle (PHEV)” categories throughout 2019 (EEA, 2020).

The share of EV users in Europe has moved beyond 2.5%–4.2% in 2019 (IEA, 2019). Combined EV adoption targets have been set by the European commission across each member states to reach 9–10 million EV users on the road by the end of 2022 (McKinsey and Company, 2014). However, the shift in the global powertrain portfolio accompanies a set of sustainability-related questions, related to the power surges in the electric grid to satisfy the extra charging needs of EV adopters, the ecosystem related impacts across the EV life cycle stages, and the concerns related to material recycling and end-of-life (EoL) impacts. Furthermore, consequences related to the energy storage systems, range anxieties, impact backed with the increased use of

\* Corresponding author.

E-mail address: [mkucukvar@qu.edu.qa](mailto:mkucukvar@qu.edu.qa) (M. Kucukvar).

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Abbreviations		kWh	Kilowatt-hour
Symbol	BEV	LC	Life cycle
	CCR	LCA	Life cycle assessment
	CO <sub>2</sub>	LCC	Life cycle costing
	DEA	LCSA	Life cycle sustainability assessment
	DMU	PHEV	Plug-in hybrid electric vehicle
	EEA	SBM	Slacks-based Measure
	E-LCA	SDG	Sustainable development goal
	EoL	SO <sub>2</sub>	Sulfur dioxide
	EU	SLCA	Social-Life cycle assessment
	EV	CI	Cluster index
	EV-LCA	SCI	Sum of cluster index
	FCEV	TBL	Triple Bottom Line
	GHG	TTW	Tank-to-Wheel
	HEV	UK	United Kingdom
	ICV	US	United States
	JRC	WTT	Well-to-Tank
		WTW	Well-to-Wheel

low-carbon sources in the power mix (Onat and Kucukvar, 2020), and active conditioners have all resulted in taking steps to pioneer the technology with a touch of sustainability science throughout the life cycle. With regard to the replacement of conventional vehicles by EV, Ghosh (2020) concludes that BEVs are considered a true zero-emission vehicle due to the lack of tailpipe emissions compared to other types of EV, but the savings in greenhouse gas (GHG) emissions from the EV is debatable when the energy required to charge the EV comes from traditional sources of fossil fuels, as it also alludes to the technical, economic, and logistical barriers that stop the expansion. The environmental impact of BEVs is contingent on the extent to which electricity used by the vehicles is produced in an environment-friendly manner. If the electricity is produced mainly using fossil fuels, BEVs may report higher GHG emissions than ICEVs. Szinai et al. (2020) estimate the integration of EV in the state of California, United States, by 2025. This analysis ensures that the fusion EV and renewables will help to decarbonize both the transport and electricity sector simultaneously. Li and Chang (2019) carried out a study of electric mobility in the Asia Southeast, involving the fleet of residential passengers, buses, and trucks. This evaluation includes availability, applicability, acceptability, and affordability indicators, giving a final energy consumption and major energy security. Raugei et al. (2018) affirmed that the EV integration can reduce significantly the UK's dependence on conventional primary energy sources. The analyzed key-metric is the demand for non-renewable energy, which could be reduced by around 34% by EV in comparison to conventional vehicles. The mitigation of emissions, studied by Nichols et al. (2015) in the state of Texas (United States), demonstrates the substantial reduction of greenhouse gases to be achieved by renewable integration into mix generation power systems. Vehicles powered by coal, natural gas, and renewables are compared to EVs, highlighting that EVs reduce significantly emissions and increase energy security. Understanding the generation mix of the power system is thus necessary to efficiently integrate EV into the residential fleet.

### 1.2. Life cycle assessment for electric vehicles

The switch towards carbon-neutral mobility practices has reshaped the automotive landscape to better understand the associated environmental impacts to avert the switch of the burden from one stage to the other across the life cycle (Elhmoud and Kutty, 2020). Life cycle studies on EVs mainly cover impact categories, including air quality impacts on human health, ecosystem health, and climate change (Onat et al., 2017). Studies on electric vehicle LCA have acknowledged contributions in

these impact categories. In addition, they have attempted to investigate whether the deployment of these alternative technologies offers promising benefits in terms of cost and impact reduction from a day-to-day perspective across the life cycle or not.

Electric vehicle life cycle assessment (EV-LCA) is a time-tested multimedia assessment technique used to calculate the ecological impacts and estimate the resource consumption for EV using a life cycle thinking approach (Onat et al., 2015; Kutty et al., 2020). The EV-LCA studies often branch out into two prime assessment categories: Fuel life cycle analysis (F-LCA) and vehicle-based LCA approach (Onat et al., 2019). Several studies have been developed and applied in the area of EV-LCA over the years. For example, Lucas et al. (2012) carried out a well-to-wheel fuel LCA analysis to quantify the energy utilization and carbon emissions from manufacturing, maintenance, and scrapping of fuel supply support infrastructures for EV and ICVs in Portugal. While, a combined LCA approach using PCO-CENEX drive cycle considering F-LCA, that consist of "Tank-to-Wheel (TTW)" and "Well-to-Tank (WTT)" approach and, vehicle LCA using a "cradle-to-grave (CTG)" approach for vehicle material related consumption was studied by Baptista et al. (2011). The results revealed that fuel cell-powered London passenger taxis consumed less energy than the diesel-powered ICV and electric propelled EVs. Similarly, a comparative approach with E-LCA combined with cost analysis from a CTG perspective using the Well-to-Wheel (WTW) analysis for fuel supply on Lithuanian passenger vehicles was carried out by Petrauskienė et al. (2021). As a result, low-carbon energy in the electricity mix for BEVs proved to neutralize the environmental impacts considerably, while simultaneously, the BEVs and ICVs proved to be cost-effective throughout the total life cycle use phase.

Naranjo et al. (2021) conducted a comparative LCA utilizing the CTG approach to quantify the potential climate change-related impacts during the use of Spanish passenger vehicles. Multiple impact categories and energy scenarios across time were taken into account for a BEV lifetime of 150,000 km. The energy projection scenario results revealed a considerable reduction in CO<sub>2</sub>-eq emissions up to 27.41% by using renewable electricity sources in BEVs by 2050. A similar study was carried out earlier by Yang et al. (2020) for Chinese passenger vehicles, including ICV, BEV, and PHEV, evaluating the particulate emissions across the entire vehicle LC stages. The study found PM<sub>2.5</sub> and Sulfur dioxide (SO<sub>2</sub>) high when using the renewable energy source with biomass share compared to the emission statistics obtained for ICEVs. Xiong et al. (2021) conducted a hybrid LCA to understand the emission reduction potential for the complete electrification of passenger cars in mainland China. The study identified a lack of potential in reducing CO<sub>2</sub>

emissions by the electrification of passenger cars in China since the emissions released during the vehicle manufacturing phase outweigh the emission saved on the road by the EV deployment. While the use of renewable energy sources in fuel cell technologies has resulted in considerable reductions in footprint-related emissions up to 70%, as identified through the LCA study conducted by Usai et al. (2021) for fuel cell electric vehicles (FCEV). An electricity system model integrated with LCA was used by Xu et al. (2020) to identify the difference in the impacts generated while utilizing several charging strategies for EVs in Europe. Prolonged vehicle-to-grid charging strategies resulted in load issues and impacts associated with overload on the power grid system. These studies play a pivotal role in structuring policies to meet air quality directives and support commitments laid to accomplish emission reduction targets.

### 1.3. Efficiency assessment using DEA

Data Envelopment Analysis (DEA) is a mathematical model used to assess the relative efficiency and performance of a set of “decision-making units (DMU)” using linear programming (Shao et al., 2019). The technique differs in which the DMUs freely choose from a set of inputs and outputs to minimize the associated impacts and maximize the relative efficiency (Sueyoshi and Yuan, 2015). Different from the traditional empirical models such as the regression analysis is the ability of DEA to arbitrarily assign weights to the sustainability indicators to estimate the efficiency of DMUs (Kutty et al., 2020a). As shown in the results of using the DEA technique, the relative efficiency for each of the comparable units appears as a non-negative score within the range of 0–1 (Zurano-Cervelló et al., 2019). The efficiency scores translate that each DMU performs relative to the inputs they consume for the set of output units they produce, determining how best performing each unit is compared to similar functional units.

DEA has long been used to assess the sustainable performance and the associated energy efficiency of comparable units across several research areas over the years (Ezici et al., 2020). Fathi et al. (2021) used an integrated bargaining “game cross-efficiency DEA model” to understand the energy efficiency performance of fossil fuel exporting nations worldwide. The countries were ranked based on the Nash equilibrium bargaining payoff points to find the most energy-efficient nation. Zhang et al. (2021) used an improved window DEA to analyze the cross-sectional energy efficiency of countries in western Europe. To acknowledge the optimal use of innovation strategies in energy management and assess the environmental performance of energy R&D expenditure in developing countries, a “bootstrap DEA analysis” was used by Koçak et al. (2021). The study adds an empirical assessment to show the improvement path for inefficient countries as well. At the same time, a game theory-based “cross-efficiency DEA model” with the Malmquist productivity index was used for Chinese utility sector efficiency calculation by Xie et al. (2021).

DEA being a powerful analytical technique, has not failed to extend its application to address concerns in the transportation sector (Neves et al., 2020). A parallel DEA model was applied to evaluate the integrated ecological efficiency for the passenger transportation system in China by Liu et al. (2020). A convergence analysis was used to capture the significant difference between the groups of performing units. Kucukvar et al. (2020) conducted an eco-efficiency performance assessment on 30 international airports around the world using a frontier-based DEA model taking into account the triple bottom line sustainability aspects. The carbon efficiency as a result of the governmental regulations on the Chinese transportation sector was evaluated using a “Slacks-based Measure (SBM) DEA model” by Chang and Zhang (2017). The results revealed adhering to the opportunity cost so as to reduce the carbon dependency. While, an SBM-DEA model with undesirability factors was used to understand the environmental efficiency of the Chinese traffic network in 30 provinces of mainland China by Song et al. (2015). Application of several modified DEA models can be seen in

the studies conducted by Ibrahim and Daneshvar (2017) for supply chain performance assessment, Ru and Si (2015) to calculate energy efficiency in the sugar cane industry, and Zhang and Wang (2010) for project selection process efficiency evaluation.

### 1.4. Novelty and contribution to the state-of-art

Considering previous contributions aiming to decarbonize the residential transport sector, determination of environmental efficiency level in the use of BEVs is important for countries, under various production mix scenarios to accelerate large-scale adoption of EVs in the market. Accounting to this, the research presented aims to conduct a scenario-based analysis on the environmental efficiency of European countries using restricted and non-restricted DEA models under various production mix scenarios. This research stays as a backbone in signaling action plans to accelerate the EU-wide large-scale EV adaption to support sustainable mobility by understanding the synergies between average electricity mix (2015), marginal electricity mix (2015–2020), and renewable energy-based electricity mix (2030–2040) for each of the EU member states used for powering the BEVs. As seen in the review, previous studies were conducted across the United States, South East Asia, and other parts of the world with a small sample size, where this research is the first of its kind assessment for 27 EU member states, along with the well-to-wheel environmental life cycle analysis of BEVs. Similarly, the studies to date have focused on several life cycle approaches and efficiency evaluation techniques for EV sustainability assessment using non-parametric approaches such as the Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). DEA assigns relative weights to the indicators using mathematical programming. Due to the use of unrealistic input and output weights assigned by linear programming, the discrimination power of the traditional DEA model is considerably reduced in some cases. Constraints on weights can be included in the model to eliminate the possibility of the DMUs having a high-efficiency score, thus raising the model’s discrimination power and eliminating any possible bias in the efficiency results. The implicit weighting using DEA and expert judgment-based weights were used to evaluate and compare the footprint efficiency results of different electricity production mix scenarios for the first time in this research. The panel-based weights obtained from the survey of the European Commission’s Joint Research Center (JRC) are used to model the environmental efficiency. This helps to understand the change impact on each EU member state’s efficiency, supporting unbiased decision making. To sum up, this paper presents a holistic and integrated decision-making model by combining the non-parametric frontier model with environmental life cycle assessment for environmental efficiency of electric vehicles based on past, present, and future electricity production mixes of each European country. On all account, this research aims to cover the following objectives to broaden the scope of EV environmental sustainability assessment across Europe, namely;

1. Conduct a scenario-based analysis for average power mix (base year), marginal electricity mix (2015–20), and renewable electricity mix (2030–2040).
2. Develop environmental efficiency assessment models for the operational environmental performance of battery electric vehicles across Europe.
3. Build a weighted and non-weighted Charnes, Cooper, and Rhodes (CCR)-DEA model to analyze the environmental efficiency of battery electric vehicles based on their well-to-wheel life cycle performance.
4. Propose policy recommendations for each country for environmentally sustainable electric vehicle deployment related to the present and future electricity production mixes.

The rest of the paper is divided into the following sections: Section 2 describes in detail the proposed method for environmental efficiency

assessment under several electricity production mix scenarios using weighted and non-weighted DEA models combined with the WTW-LCA method. Section 3 discusses the results of the analysis in terms of efficiency scores, along with the results of the projection level analysis and model-based variability assessment with grouped performance. Finally, conclusions and future directions are given in Section 4.

## 2. Methods

This paper uses the Well-to-Wheel (WTW) LCA method combined with the weight restricted and unrestricted DEA model to bring out the environmental efficiency values for each of the 27 European countries. The research undertakes the following structure to accomplish the desired results in assessing the environmental efficiency of European countries towards the use of BEVs. The research makes use of the latest ecoinvent v3.7 life cycle impact database (Vandepaer et al., 2019). The midpoints environmental impacts per kWh of electricity generation are estimated for each of the 27 European countries. After estimating the per kWh environmental footprints for the electricity generation per country, the wheel-to-wheel environmental impacts of BEVs are calculated based on the functional unit per km traveled.

A CCR-based weighted DEA model is then run using the panel-based weights obtained from the survey of the European Commission's recent report to model the environmental efficiency (Sala et al., 2018). First, the footprint-based efficiency related to different electricity production mix scenarios is identified. It is then compared with the nonrestricted and weight-restricted DEA model results. Next, a scenario-based comparison is carried out, followed by a future projection analysis to improve the environmental efficiency of BEVs. An environmental efficiency performance grouping is then done using the quartile method to identify the grouped performance scoring for each country. Finally, a model-based variability assessment using the Kruskal-Wallis H test is undertaken, supported with a projection level analysis. Fig. 1 presents the integrated research method in a step-by-step manner.

### 2.1. Well-to-wheel (WTW) analysis

WTW is an LCA method used in calculating the energy utilization and the associated emissions from the powertrain, starting from the extraction phase of the energy system (Well) to the utilization point (Wheel). The analysis captures the tailpipe emissions and gives an entire picture of the emissions along the fuel cycle's manufacturing, transportation, and distribution pathways. BEVs do not emit exhaust-based emissions along with their operation phase. Thus, sustainability assessment for BEVs depends on the source of the energy mix used during their life cycle (Onat et al., 2017b). The WTW analysis can be split into two sub-phases: the WTT approach and the TTW approach (see Fig. 2). The WTW analysis accounts for the indirect emissions across the entire fuel chain and not along the drive cycle. At the same time, the TTW accounts for the emissions during the driving phase of BEVs. If  $j$  represents the environmental impact categories then, the associated emission along the assessment stage for the  $j$ th category is calculated using Eq. (1) as follows:

$$E_j = EV_{cc} \times [TTW_j + WTT_j] \quad (1)$$

where;

$EV_{cc}$  = electric vehicle charge consumption expressed in kWh/km.

$TTW_j$  = energy consumption in kWh for the  $j$ th impact category across the drive cycle.

$WTT_j$  = energy consumption in kWh for the  $j$ th impact category associated with the electricity generation phase.

Per km travel is taken as the functional unit for the WTW assessment.

The associated environmental impacts vary based on the power generation, trends in driving patterns, and weather-related uncertainties (Alghoul et al., 2018). In addition, the upstream and downstream energy consumption-related impacts vary based on the source used for the power generation (Kucukvar et al., 2017, 2018). The data for the electricity generation mix is presented in Fig. S1 (Supporting Information (SI) file) was collected from the ecoinvent v3.7 life cycle impact

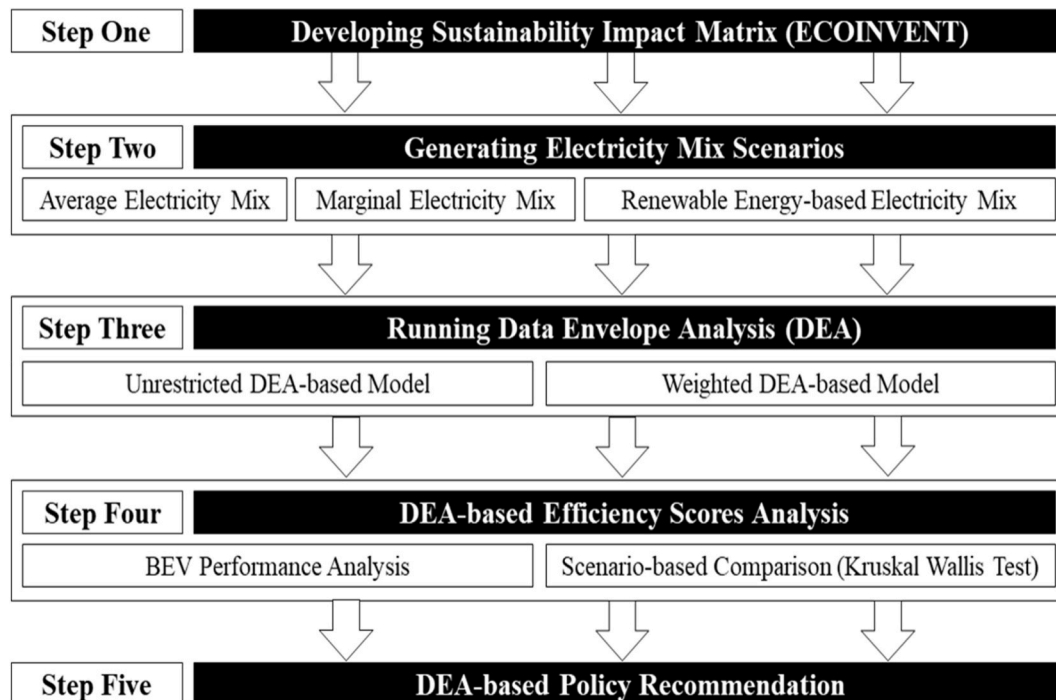


Fig. 1. Research flow diagram.



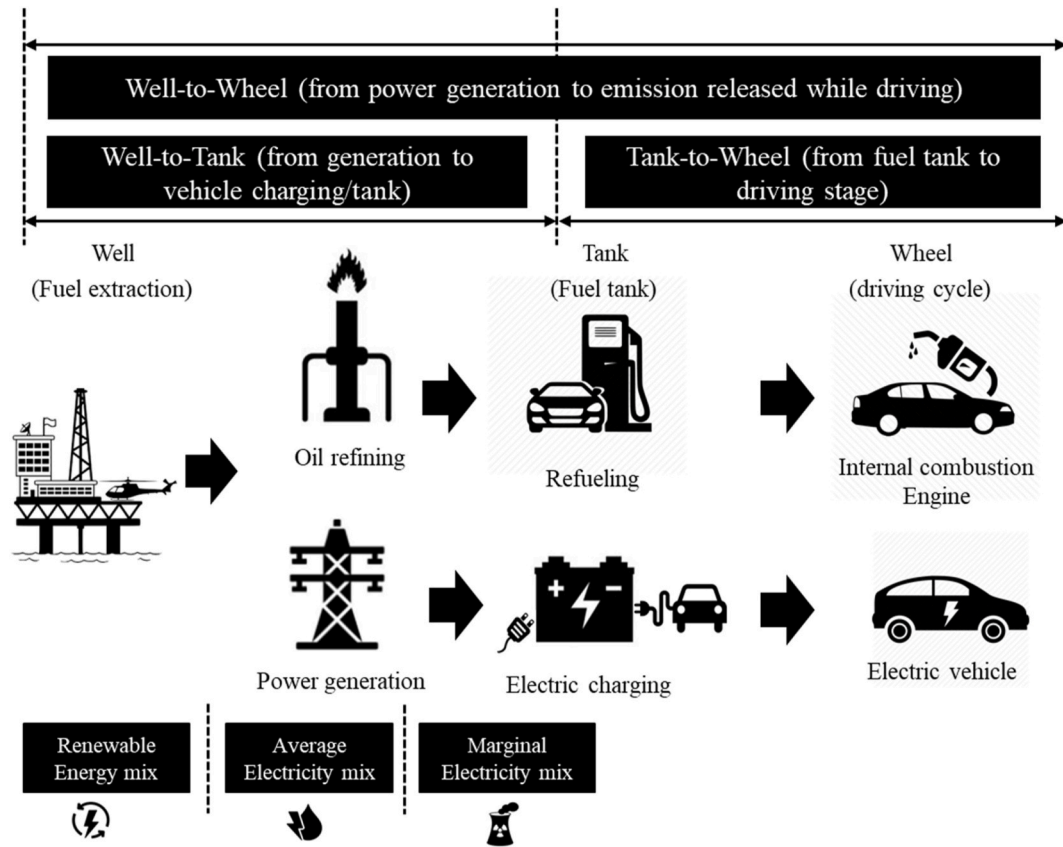


Fig. 2. Schematics for a WTW analysis.

database across three periods: average electricity mix (2015), marginal electricity mix (between 2015 and 2020), and renewable energy-based electricity mix (between 2030 and 2040).

The average impact factors per kWh electricity generation by a source according to the life cycle impact data were collected from the latest ecoinvent v3.7. The environmental impacts of per kWh electricity generation included several phases such as raw material extraction and processing, operation and maintenance, and construction activities. Similarly, the data for all the impact categories were obtained from the ecoinvent v3.7 database. The battery-operated electric vehicle brand “Nissan Leaf” was used to study the associated impacts. The average electricity consumption for the selected BEV is 18.7 kWh/100 km (Helmets and Marx, 2012). Considering the values for the average electricity mix, marginal electricity mix, renewable energy-based electricity mix, and the associated impact categories mentioned in the Supplementary Information File (see Tables S1–3), the WTT impacts were calculated using equation (2) as;

$$WTT_{jk} = \sum (P_{sk} \times E_{js}) \quad (2)$$

where;

$j_k$  =  $j$ th impact category for the  $k$ th country.

$P_{sk}$  = percentage value for the power generation source ( $s$ ) in the  $k$ th country.

$E_{js}$  = environmental impact for  $j$ th category per source  $s$ .

The values of water consumption (L/kWh) and GHG emissions (g/kWh) are zero due to no direct emissions in the TTW stage. The environmental impact categories included climate change (kg CO<sub>2</sub>-Eq/kWh), freshwater ecotoxicity (kg 1,4-dichlorobenzene (DCB)-Eq/kWh), freshwater eutrophication (kg P-Eq/kWh), human toxicity (kg 1,4-DCB-Eq/kWh), metal depletion (kg Fe-Eq/kWh), particulate matter formation

(kg particulate matter (PM)<sub>10</sub>-Eq/kWh), photochemical oxidant formation (kg non-methane volatile organic compounds (NMVOC)/kWh), terrestrial acidification (kg SO<sub>2</sub>-Eq/kWh), and urban land occupation (square meter-year/kWh).

## 2.2 Input-oriented DEA model.

A constant-return-to-scale model developed by (Charnes et al., 1978), known as CCR, and a variable return-to-scale model developed by Banker et al. (1984) are the two DEA models used commonly when computing relative efficiency scores for decision-making units. This study uses the input-oriented CCR model due to the robust efficiency measures delivered by the model under realistic scenarios (Supciller and Bulak, 2020). With the aim to cut down the environmental impacts under the triple bottom line umbrella for the member states to be efficient in their use of EVs. For that reason, the first model, which is the IO-DEA multiplier model, was used in the study.

Consider  $x_j$  and  $y_k$  as the  $j$ th input and  $k$ th output for the respective DMU under evaluation. To estimate the relative efficiency, the ratio between the weighted output (WO) and the weighted input (WI) is used as proposed in the studies of (Onat et al. 2017 a,b). The environmental efficiency is computed using Eq. (3) as;

$$\xi = \frac{WO}{WI} = \frac{\sum_{k=1}^q \mu_k y_k}{\sum_{j=1}^p \nu_j x_j} \quad (3)$$

where;

$p$  = number of input DMUs

$q$  = number of output DMUs.

$\nu_j \geq 0$  = weights assigned to the  $j$ th input.

$\mu_k \geq 0$  = weights assigned to the  $k$ th output.

The DMU's weights,  $\nu_j$  and  $\mu_k$  are arbitrarily chosen by linear programming. The proposed DEA model is as follows (Eqs. (4)–(6));

## Objective Function

$$\max z = \frac{\sum_{k=1}^q \mu_k y_k}{\sum_{j=1}^p v_j x_j} \quad (4)$$

Subject to;

$$\max z = \frac{\sum_{k=1}^q \mu_k y_k}{\sum_{j=1}^p v_j x_j} \leq 1, j = 1, \dots, N \quad (5)$$

$$\mu_k, v_j \geq 0 \quad (6)$$

where;

 $x_{ij}$  and  $y_{ki}$  =  $j$  th input and  $k$ th output of the  $i$ th DMU. $Z$  = total number of DMUs.

DMU <sub>$j$</sub>  is considered efficient if the value of the objective function  $z$  (Eq. (4)) is 1. If the value is found to be less than 1, the DMU <sub>$j$</sub>  is considered inefficient where the inputs of DMU <sub>$j$</sub>  were not able to reach a sufficient level producing the output for other DMUs.

## 2.2. Weighted and non-weighted DEA model

The non-weighted DEA model arbitrarily assigns weights that maximize the efficiency scores for each DMU and provides flexibility in determining these weights (Egilmez et al., 2013). This flexibility enables different input and output weights of different DMUs, thus eliminating the need to obtain a common weight set for all decision-making units.

$$V_{climatechange} \geq V_{particulatematterformation} \geq V_{metaldpletion} = V_{urbanlandoccupation} \geq V_{photochemicaloxidantformation} \geq V_{humantoxicity} = V_{terrestrialacidification} \geq V_{freshwatereutrophication} \geq V_{freshwaterecotoxicity} \quad (15)$$

Due to the flexibility provided by the non-weighted DEA in determining weights, the discrimination power of the model is considerably reduced in some cases (Egilmez et al., 2016). The discrimination power of the model decreases inputs, and output indicators are included in the evaluation set. In this context, to raise the discrimination power of the model, it may be preferable to include more decision-making units in the analysis or to eliminate some of the input and output variables from the analysis (Dyson et al., 2001). However, in some cases, it is not possible to achieve this condition. Another way to raise the discrimination power of the model is by adding constraints on the weights for the model. In other words, since unrealistic input and output weights are used, constraints on weights can be included in the model as a way of eliminating the possibility of the DMUs having a high-efficiency score (Mavi et al., 2019). Therefore, the DEA may be adjusted to alleviate the subjective evaluation of the weights of the inputs (environmental impact categories) and outputs (economic performance variables), while the conventional DEA does not necessitate an initial weight assignment (Pan et al., 2021). In this context, two different approaches were put in place to identify and compare the different consequences. Besides the conventional approach, a weight-restricted model was adopted in the environmental efficiency analysis of electrical vehicles. Eq. (4) is converted into a mathematical programming model by multiplying the inverse function of the environmental efficiency ratio to form Eq. (5), subject to the constraints Eq. (8) and Eq. (9).

$$\min z^{-1} = \frac{1}{Y_j} \times \sum_{i=1}^m v_i x_{ij} \quad (7)$$

Subject to

$$\frac{1}{Y_j} \times \sum_{i=1}^m v_i x_{ij} \geq 1, j = 1, \dots, N \quad (8)$$

$$v_r \geq 0 \quad (9)$$

$Y_j$  is the per km traveled by the DMU <sub>$j$</sub> . This model does not require any multipliers due to the existence of a single output. The weight-restricted model (Eq. (10)) helps us identify whether discrimination limits the capacity of the DEA model to bring efficient results compared with the traditional model for the envelopment analysis. Weights for certain impact categories are assigned through estimation even after the weight restriction as per equations (11)–(14). This model reads as follows:

$$\min z^{-1} = \frac{1}{Y_j} \times \sum_{i=1}^m v_i x_{ij} \quad (10)$$

Subject to

$$\frac{1}{Y_j} \times \sum_{i=1}^m v_i x_{ij} \geq 1, j = 1, \dots, N \quad (11)$$

$$\alpha_j v_1 - v_j \geq 0, j = 2, 3, \dots, s \quad (12)$$

$$\beta_j v_1 - v_j \leq 0, j = 2, 3, \dots, s \quad (13)$$

$$v_r \geq 0 \quad (14)$$

where  $\alpha_j$  and  $\beta_j$  are positive scalars. Weights gathered from the European Commission's Joint Research Center (Sala et al., 2018) are used to denote the constraint (Eq. (15)) given as follows:

Table 1

Proposed DEA models under each energy source with selected inputs and outputs.

DEA Models	Energy Source	Inputs	Unit	Output
Scenario-1	Average electricity mix (2015)	Climate change	kg CO <sub>2</sub> -Eq/kWh	Per-Km Travel
Scenario-2	Marginal electricity mix (2015–20)	Freshwater ecotoxicity	kg 1,4-DCB-Eq/kWh	
Scenario-3	Renewable energy-based electricity mix (2030–40)	Freshwater eutrophication	kg P-Eq/kWh	
WScenario-1	Average electricity mix (2015)	Human toxicity	kg 1,4-DCB-Eq/kWh	
WScenario-2	Marginal electricity mix (2015–20)	Metal depletion	kg Fe-Eq/kWh	
WScenario-3	Renewable energy-based electricity mix (2030–40)	Particulate matter formation	kg PM10-Eq/kWh	
		Photochemical oxidant formation	kg NMVOC/kWh	
		Terrestrial acidification	kg SO <sub>2</sub> -Eq/kWh	
		Urban land occupation	square meter/year/kWh	

The weights are assigned to each of the midpoint impact categories by the expert panel using the elicitation techniques and “value choice” method based on the most critical impact categories and elementary flows to reach a consensus in assigning the weights. The assigned weights by the expert panel to each of the impact categories can be found in [Sala et al. \(2018\)](#). The primary objective in running a weight-restricted DEA model is to arbitrarily manage the efficiency level of the DMUs and undertake a comparison between the weight-restricted and unrestricted DEA models. Therefore, assigning weights by the experts to the impact categories can greatly impact the efficiency outcomes for each DMU. [Table 1](#) shows all the six DEA models categorized into weighted and non-weighted scenarios along with the inputs and outputs. All the environmental impact categories namely; Climate change, Freshwater eco-toxicity, Freshwater eutrophication, Human toxicity, Metal depletion, Particulate matter formation, Photochemical oxidant formation, Terrestrial acidification, and Urban land occupation were considered as inputs and, per-km travel as the output for all the six DEA

models considered in the study. Three different analyses were carried out for both the weighted and non-weighted scenarios using an input-oriented DEA model.

### 2.3. Non-parametric test for variability assessment

Kruskal-Wallis H test, a non-parametric test is used to determine the significant difference in the *mean  $\xi$  score* across each scenario outlined in the study. The test draws the assumption that the samples are randomly distributed. The null hypothesis ( $H_0$ ) for the Kruskal-Wallis H test is that the *mean  $\xi$  score* is equally distributed to the alternative hypothesis ( $H_A$ ) that there exists at least one  $\xi$  score significantly different from the overall sample. The test hypothesis can be represented as;  $H_0 = \mu_{\xi(1)} = \mu_{\xi(2)} = \dots = \mu_{\xi(6)}$  and  $H_A = \mu_{\xi(1)} = \mu_{\xi(2)} \neq \mu_{\xi(3)} = \dots = \mu_{\xi(6)}$ ; where  $\mu_{\xi(j)}$  is the *mean  $\xi$  score* for the  $j$ th Scenario. The Kruskal-Wallis H test statistics can be calculated using Eq. (16) as follows;

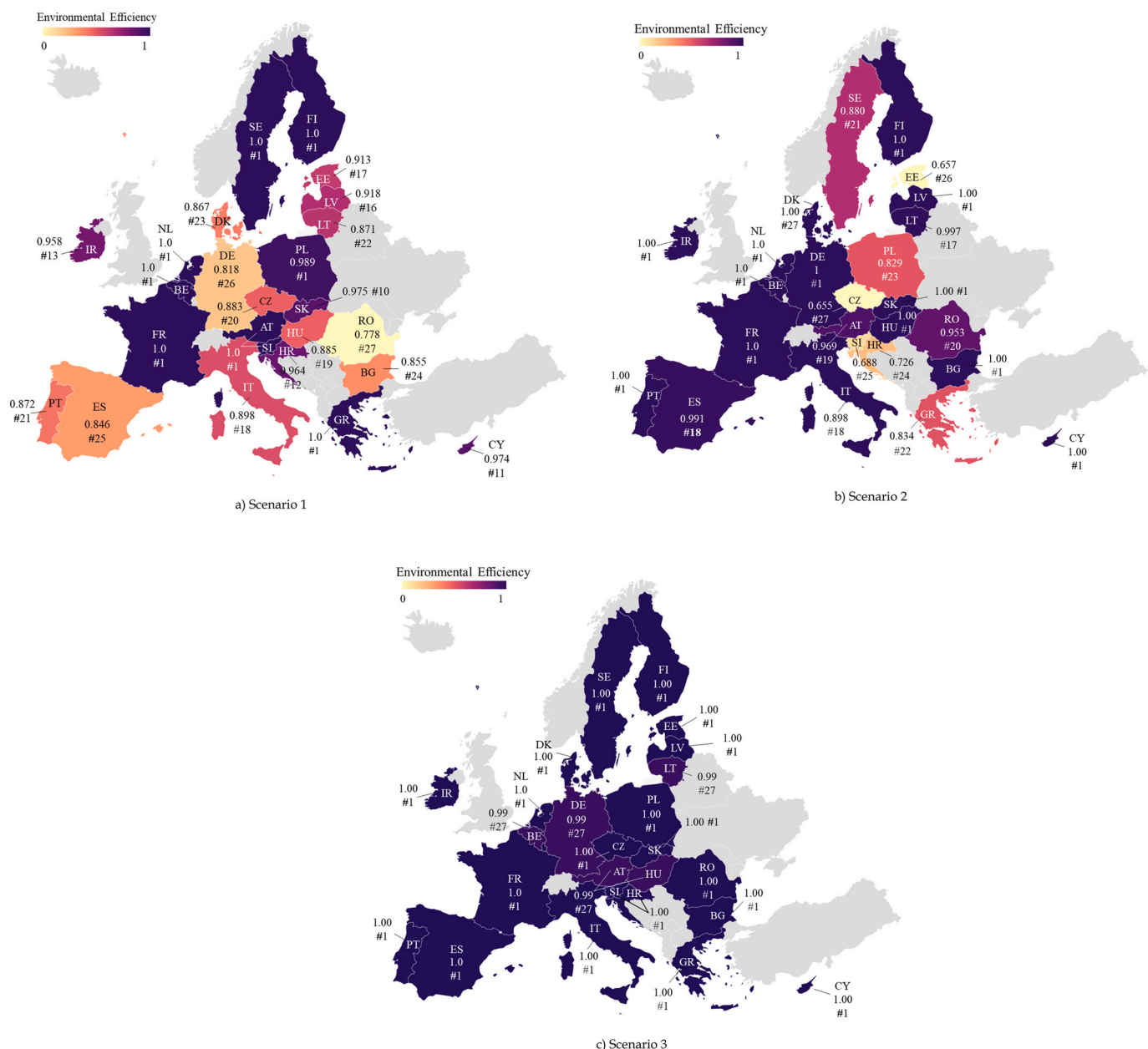


Fig. 3. Environmental efficiency and ranking results of BEVs under a non-restricted model for a) Scenario 1; b) Scenario 2; c) Scenario 3.



$$H = \frac{\sum_{all j} (\bar{X}_j - \bar{X}) (Z - 1)}{\sum_{all j} \sum_{k=1}^{n_j} (X_{jk} - \bar{X})^2}; \text{ For } j = 1, 2, \dots, 6 \quad (16)$$

where;

$n_j$  = DMUs tested under the  $j$ th Scenario.

$Z$  = total number of DMUs considered in the study.

$X_{jk}$  = rank of  $k$ th observation under the  $j$ th Scenario.

$\bar{X}_j$  = average rank for the  $j$ th Scenario.

$\bar{X}$  = average rank across all the scenarios considered in the study.

To determine whether the *mean  $\xi$  score* across each scenario varies significantly, a 95% significance level represented by  $\alpha = 0.05$  is chosen to compare the estimates with the p-value. If p-value  $> \alpha$ , the H statistics is insignificant. Thus, we fail to reject  $H_0$ . This translates to the fact that the *mean  $\xi$  score* across each scenario is insignificantly different from each other. On the contrary, if the p-value  $\leq \alpha$ , there is sufficient evidence to prove that the *mean  $\xi$  score* across each varies significantly from

each other. Pairwise comparison is used to identify the set of scenarios with similar  $\xi$  scores. The combination for each scenario for a pairwise comparison is calculated using Eq. (17);

$$C_r^n = \frac{n!}{(n-r)! r!}; \text{ For } n = 6 \text{ and } r = 2 \quad (17)$$

where;

$n$  = number of scenarios

$r$  = number of subsets under comparison.

### 3. Results and discussions

#### 3.1. Unrestricted DEA model

This section attempts to explain the analysis conducted for all six scenarios. Fig. 3 shows the relative environmental efficiency score ( $\xi$ )

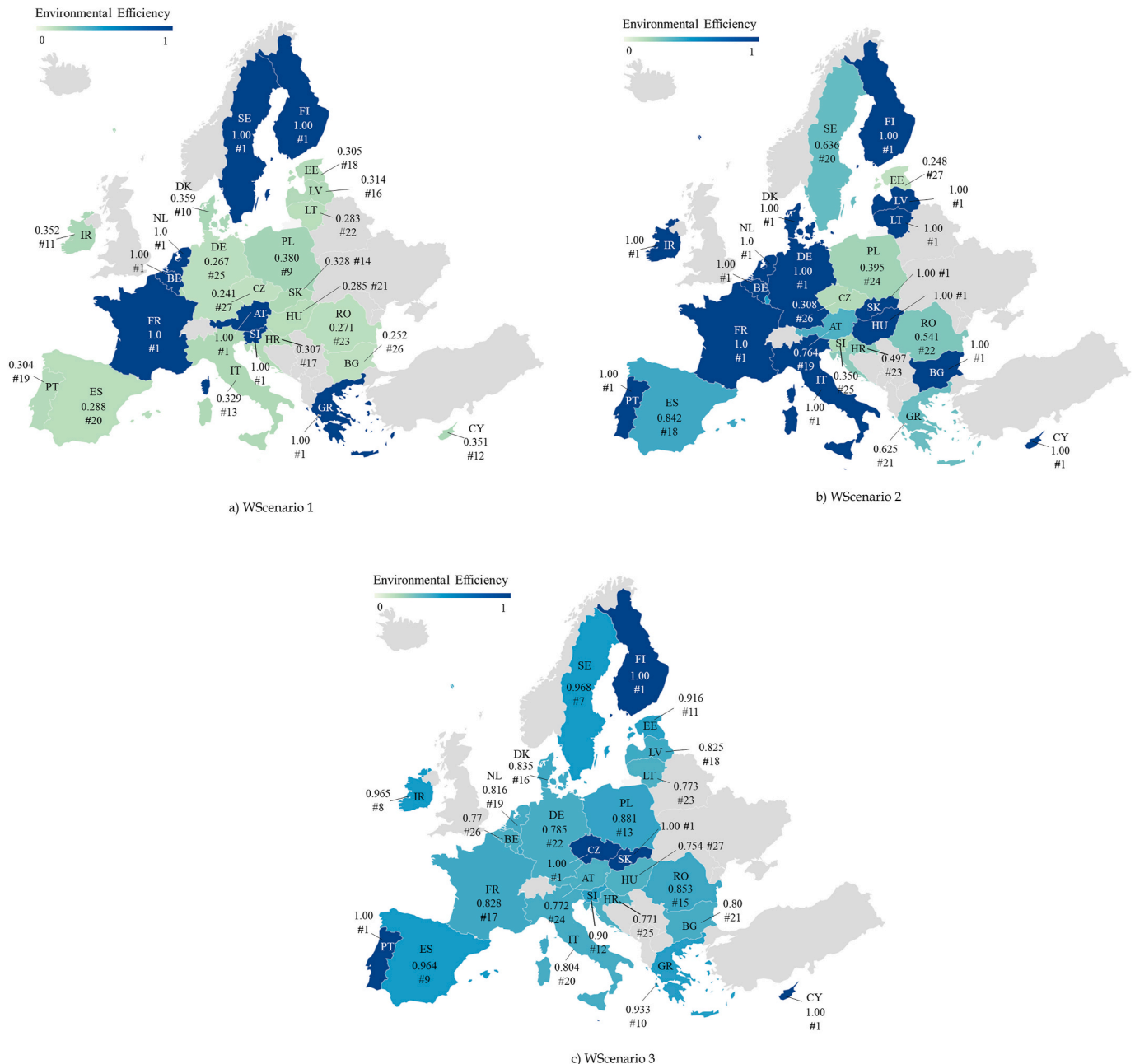


Fig. 4. Environmental efficiency and ranking results of BEVs under weight restricted model for a) WScenario 1; b) WScenario 2; c) WScenario 3.

under all the Scenarios (Scenario 1, Scenario 2, Scenario 3) for each European member state. The results appear as a non-negative score within the range from 0 to 1. Each European country is ranked in the ascending order of its performance under Scenario 1, as shown in Fig. 3. It is seen under Scenario 1 that Romania performs the least in terms of environmental efficiency with an efficiency score  $\xi = 0.7781$  relative to other comparable units. The reason might account for the decreased shares of renewable energy sources and of natural gas combined-cycle plants in Romania, explaining the tendency towards lower impact and efficiency scores. The impacts of the average electricity mix are generally more spread out in comparison to the marginal mix. This is due to the extreme value caused in some categories by harmful fossil-fired units whose shares are significantly lower in the average mixes.

On the other hand, European countries like Slovenia, Sweden, Netherlands, Greece, France, Finland, Belgium and, Austria were ranked among the top with an efficiency score  $\xi = 1$ . When, Netherlands, France, Finland, and Belgium retained their position under Scenario 2 (Fig. 3) as the most environmentally efficient countries in terms of their use of EVs, Slovenia, Sweden, Greece, and Austria were pushed out of the list to fall under the medium-to-low efficiency categories. Scenario 2 witnessed the Czech Republic as the least performing unit with an efficiency score of  $\xi = 0.6554$ . The reason for the least efficient performance of the Czech Republic can account for the biggest difference between average and marginal mix, in terms of impacts. The scores of the marginal mix are mostly due to the vast share of foreign imports, with both relying on fossil-fired units for a large share of their mix, and shares stemming from fossil heat and power co-generation units. In terms of its relative efficiency under scenario 1, Romania, the least performing country, showed considerable improvement under scenario 2 ( $\xi = 0.9531$ ). Despite the improvement, Romania still falls under the “fairly good” performing category in the medium efficiency zone. Under this scenario, Slovakia, Portugal, Malta, Latvia, Lithuania, Italy, Ireland, Hungary, Denmark, Cyprus, and Bulgaria were termed environmentally efficient with an efficiency score  $\xi = 1$ .

The results for Scenario 3 show that all the European countries selected for the study except Latvia, Hungary, Germany, Belgium, and Austria are efficient with an efficiency score of  $\xi = 1$ . Under Scenario 3, most of the European countries showed meritorious performance compared to the least performing countries. However, the least performing countries under scenario 3 do hold a fairly high-efficiency score ( $\xi = 0.999$ ) compared to the least performing countries in Scenario 1 and Scenario 2.

### 3.2. Weight-restricted DEA model

According to the weights assigned to the impact categories, all the previous scenarios were run for the EU Electrical Vehicle environmental efficiency DEA Model. According to the analysis, Fig. 4 shows the results under the weight-restricted DEA model for WScenario 1, WScenario 2, and WScenario 3. The countries categorized as the most efficiently performing units under Scenario 1 for the non-weighted DEA model (Fig. 3) compared with the WScenario 1 remained the same. Notably, the weights assigned by the expert panel to each indicator made no difference in the efficiency outcomes in the high-performing countries. While the efficiency scores drastically fell for the remaining European countries. Under WScenario 1, the Czech Republic with an efficiency score of  $\xi = 0.241$  is the least performing European country relative to other comparable units. Despite the Czech Republic not falling on the efficient frontier under both scenarios, for Scenario 1, the country ranks 20th with an  $\xi$  score equal to 0.8834. An efficiency score of 0.8834 is fairly good in comparison with the WScenario 1 score of the Czech Republic ( $\xi = 0.241$ ). A total of 19 countries reported poor performance based on the efficiency score as the scores ranged from 0.38 to 0.241. This translates to the fact that nearly 70.37% of countries in the WScenario 1 stood way under the efficient frontier. In terms of the value-added outcomes for each of the listed countries to their environmental

burdens when accounted for relatively, certain weight assignments negatively impacted the efficiency scores of some countries.

Similarly, when comparing the efficiency results of WScenario 2 with Scenario 2 (Fig. 4), it can be seen that all the efficient countries under WScenario 2 remained the same as in Scenario 2, like the former case mentioned. Estonia, with an efficiency score  $\xi = 0.248$ , is the least efficient country in terms of using BEVs under WScenario 2. The least efficient Czech Republic under Scenario 2 was pushed to the 26th rank under WScenario 2 with an efficiency score of  $\xi = 0.308$ . The results were surprising when WScenario 3 was put under comparison with the results of Scenario 3. 81.48% of countries considered for the assessment were efficient under Scenario 3. This percentage fell, leaving Portugal, Slovakia, Malta, Finland, the Czech Republic, and Cyprus as environmentally efficient countries in BEV usage under WScenario 3. Nearly 21 countries were inefficient under this scenario. Nearly 77% of countries under the WScenario 3 can be found to be inefficient. The inefficient countries hold an efficiency score ranging from 0.968 to 0.754.

### 3.3. Model-based variability assessment

The Kruskal-Wallis H-test, as detailed in section 3.5 was used to determine the significant difference in the mean efficiency scores under all the six scenarios outlined in the study. The H statistics and p-value for the Kruskal-Wallis test were found to be 48.21 and 0.000, respectively. Based on the p-value, it is concluded that either of the scenarios dominates the other, resulting in rejecting the null hypothesis. The influence of input and output variables on the mean  $\xi$  score was studied using pairwise comparison.

Table 2 shows the pairwise comparison results of  $\xi$  score for a significance level of  $\alpha = 0.05$ . Based on the pairwise comparison results, there assumes an insignificant difference in the mean  $\xi$  score across Scenario 1 and, Scenario 2, WScenario 2, and WScenario 3. Similar results can be seen in the pairwise comparison for Scenario 2, WScenario 3, and WScenario 2, while significant difference can be seen in the mean  $\xi$  score across Scenario 1 with Scenario 3 and WScenario 1. Similarly, the pairwise comparison results show a significant difference compared to Scenario 2, Scenario 3, and WScenario 1.

**Table 2**  
Pairwise comparison on the mean  $\xi$  scores.

Analysis Category	Kruskal-Wallis	P-value	Decision	
			Insignificant	Significant
Scenario 1 Vs. Scenario 2	15.685	1.000	✓	
Scenario 1 Vs. Scenario 3	42.444	0.005		✓
Scenario 1 Vs. WScenario 1	34.944	0.050		✓
Scenario 1 Vs. WScenario 2	4.407	1.000	✓	
Scenario 1 Vs. WScenario 3	12.926	1.000	✓	
Scenario 2 Vs. Scenario 3	26.759	0.370	✓	
Scenario 2 Vs. WScenario 1	50.360	0.000		✓
Scenario 2 Vs. WScenario 2	11.278	1.000	✓	
Scenario 2 Vs. WScenario 3	28.611	0.244	✓	
Scenario 3 Vs. WScenario 1	77.389	0.000		✓
Scenario 3 Vs. WScenario 2	38.037	0.021		✓
Scenario 3 Vs. WScenario 3	55.370	0.000		✓
WScenario 1 Vs. WScenario 2	39.352	0.014		✓
WScenario 1 Vs. WScenario 3	22.019	0.967	✓	
WScenario 2 Vs. WScenario 3	17.333	1.000	✓	

**Table 3**

The percentile values using the quartile method.

Parameter	Scenario 1	Scenario 2	Scenario 3	WScenario 1	WScenario 2	WScenario 3
Minimum	0.7781	0.6554	0.9999	0.241	0.248	0.754
1st Quartile	0.8775	0.898425	1	0.28575	0.62775	0.807
25th Percentiel						
2nd Quartile	0.92425	1	1	0.317	1	0.881
50th Percentile						
3rd Quartile	0.9894	1	1	0.535	1	0.976
75th Percentile						
Maximum Score	1	1	1	1	1	1

EU Countries	Scenario 1	Scenario 2	Scenario 3	Wscenario 1	Wscenario 2	Wscenario 3
AT	1	2	3	1	2	3
BE	1	1	3	1	1	3
BG	3	1	1	3	1	3
CY	1	1	1	1	1	1
CZ	2	3	1	3	3	1
DE	3	1	3	3	1	3
DK	3	1	1	1	1	2
EE	2	3	1	2	3	1
ES	3	2	1	2	2	1
FI	1	1	1	1	1	1
FR	1	1	1	1	1	2
GR	1	3	1	1	3	1
HR	1	3	1	2	3	3
HU	2	1	3	3	1	3
IE	1	1	1	1	1	1
IT	2	1	1	1	1	3
LT	3	1	3	3	1	3
LU	2	2	1	1	2	2
LV	2	1	1	2	1	2
MT	1	1	1	3	1	1
NL	1	1	1	1	1	2
PL	1	3	1	1	3	1
PT	3	1	1	2	1	1
RO	3	2	1	3	3	2
SE	1	3	1	1	2	1
SI	1	3	1	1	3	1
SK	1	1	1	1	1	1

Key: 1= High Performance 2= Medium Performance 3=Low Performance

**Fig. 5.** Comparative performance assessment using quartile-based clustering.

### 3.4. Environmental efficiency performance clustering

This section uses the quartile method to measure the spread of the environmental efficiency scores for each DMU under the respective scenarios. The quartile-based clustering helps understand the impact of having certain output parameters in the production set on the total efficiency performance. Once the three quartiles ( $q_1$ , median, and  $q_3$ ) are calculated, each DMU is placed in the appropriate cluster (group) based on their efficiency scores. Countries that reveal efficiency scores less than the  $q_1$  are classified as “low performance”, while the countries revealing efficiency scores greater than  $q_3$  are classified as “high performance”. The others are classified as “medium performance”. Table 3

reports the percentile values using the quartile method.

Fig. 5 shows the group-based efficiency performance for each DMU under all six scenarios. To better visualize the efficiency performance, conditional formatting tends to assign position-dependent color gradient for each cluster.

The results in Fig. 5 show Finland as the most efficiently performing country in terms of their use of BEVs for all six scenarios, while France and Netherlands stand as the first runner up with a slight dip in their performance under WScenario 3. The results also show that Croatia, Malta, Poland, Sweden, and Slovenia that fell under the High-Performance cluster in Scenario 1 were pushed to the poorly performing category under WScenario 1. On the other hand, all the countries

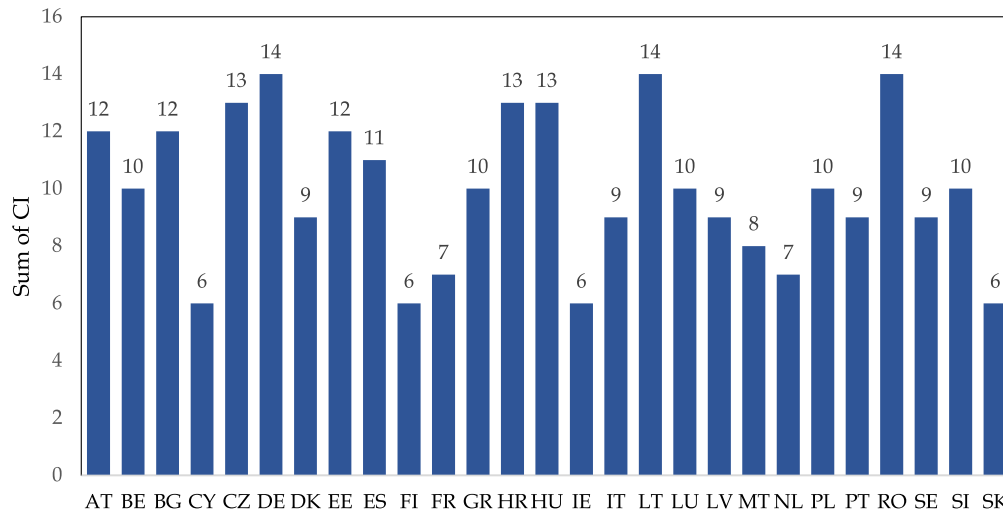


Fig. 6. Comparative performance assessment using the sum of cluster-index.

under Scenario 3 except Austria, Belgium, Hungary, and Lithuania maintained excellent efficiency scores. For general insight about the efficacy performance of the EU countries, the sum of cluster index (SCI) is used. Since index 1 refers to the “High Performance” cluster, the countries having the minimum SCI would perform better than others over all the scenarios and vice versa. The SCI can be determined using Eq. 18

$$SCI_i = \sum_{j=1}^6 CI_{ij} \quad \forall i = 1, 2, 3 \dots 27 \quad (18)$$

where  $i$  refers to the country,  $j$  refers to the scenario number, and  $CI_{ij}$  refers to the cluster-index of the  $i$ th country under the  $j$ th scenario. Fig. 6 reports the  $SCI_i$  values of the EU countries.

Considering that the “High Performance” cluster index equals one and the total number of clusters equals 6, the minimum and maximum values of the SCI are 6 and 18. Therefore, Fig. 6 shows that Cyprus, Finland, and Slovakia are the most efficient countries over the six scenarios. On the other hand, Denmark, Lithuania, Romania are the least efficient countries ( $SCI = 14$ ), followed by Hungary and Croatia ( $SCI = 13$ ).

### 3.5. Correlation analysis: efficiency versus energy prices

This section quantifies the collinearity associated between the efficiency scores and the energy prices in the EU countries. Under the context of this paper, collinearity refers to the strength of the linear relationship between the efficiency scores and electricity prices. However, the coefficient of determination is the most commonly used measure for collinearity between two variables. The  $R^2$  explains the percentage of variability in one of the model variables estimated from the other model variable. The  $R^2$  ranges from 0 to 1, quantifying the strength of the linear association between the two variables. The score of 0 indicates no correlation, while the score of 1 indicates a strong correlation. In correlation analysis, it is always important to initially evaluate the scatter plot of the two variables before computing a correlation coefficient. This is particularly useful to explore associations between the variables.

In this study, we answer our question concerning the significance of the relationship between the efficiency scores and electricity prices using the  $R^2$ -value. To continue, we set the efficiency score as the y-axis and the electricity price as the x-axes. Then, the  $R^2$  can be computed as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \bar{y})^2}{\sum_{i=1}^n (y_i - y'_i)^2} \quad (19)$$

where  $y_i$  represents the efficiency score of the  $i$ th EU country,  $\bar{y}$  represents the average of the efficiency scores, and  $y'_i$  represents the fitted value associated with  $y_i$ . The sample size  $n$  is set to the EU countries ( $n = 27$ ). Fig. 7 illustrates the fitting plot of efficiency scores and electricity prices for average power mix and marginal electricity mix (2015–2020). The dashed lines in Fig. 7 represent the fitting line (or  $y'_i$  values).

As it is noted from Fig. 7, there is a lack of linear fitting between the efficiency scores ( $y$ ) and electricity prices ( $X$ ) under the four scenarios of DEA models. The fitting line is poorly capable of representing a significant portion of the model variability. The four DEA scenarios yielded very low  $R^2$ -values, ranging from 0.095 to 0.227, which is another evidence of the lack of linearity. These findings confirm the lack of linearity between efficiency scores and electricity prices for average power mix (Scenario-1) and marginal electricity mix (Scenario-2).

### 3.6. Projection level analysis

This section attempts to carry out a projection level analysis for all the six scenarios discussed in this paper. The percentage reduction level corresponding to each environmental impact category helps understand the extent to which each indicator needs to be cut down to reach the efficient frontier. In a better sense, this analysis helps each European country move towards the sustainable use of BEVs following its best-performing peers. Table S3 shows the reference set and average projection level for Romania (RO) under Scenario 1. With an efficiency score of  $\xi = 0.7781$ , Romania is the least efficient European country compared to other countries. Austria ( $v_1 = 0.102$ ), Netherlands ( $v_2 = 0.009$ ) and Sweden ( $v_3 = 0.889$ ) were chosen as the benchmarks under this scenario. This means that Romania needs to follow the benchmarked units to achieve the average projection level to reach the desired sustainability level. The input variables for each benchmarked unit need to be multiplied by their corresponding weights for Romania to be considered efficient. Based on this analysis, Romania needs to reduce the climate change-related impacts by 84.087%, freshwater eco-toxicity by 46.48%, freshwater eutrophication by 92.379%, human toxicity by 83.477%, metal depletion by 22.19%, particulate matter formation by 92.159%, petrochemical oxidant formation by 22.19%, terrestrial acidification and urban land occupation value by 86.772% and 22.19% respectively, to improve its performance to reach the efficient frontier.

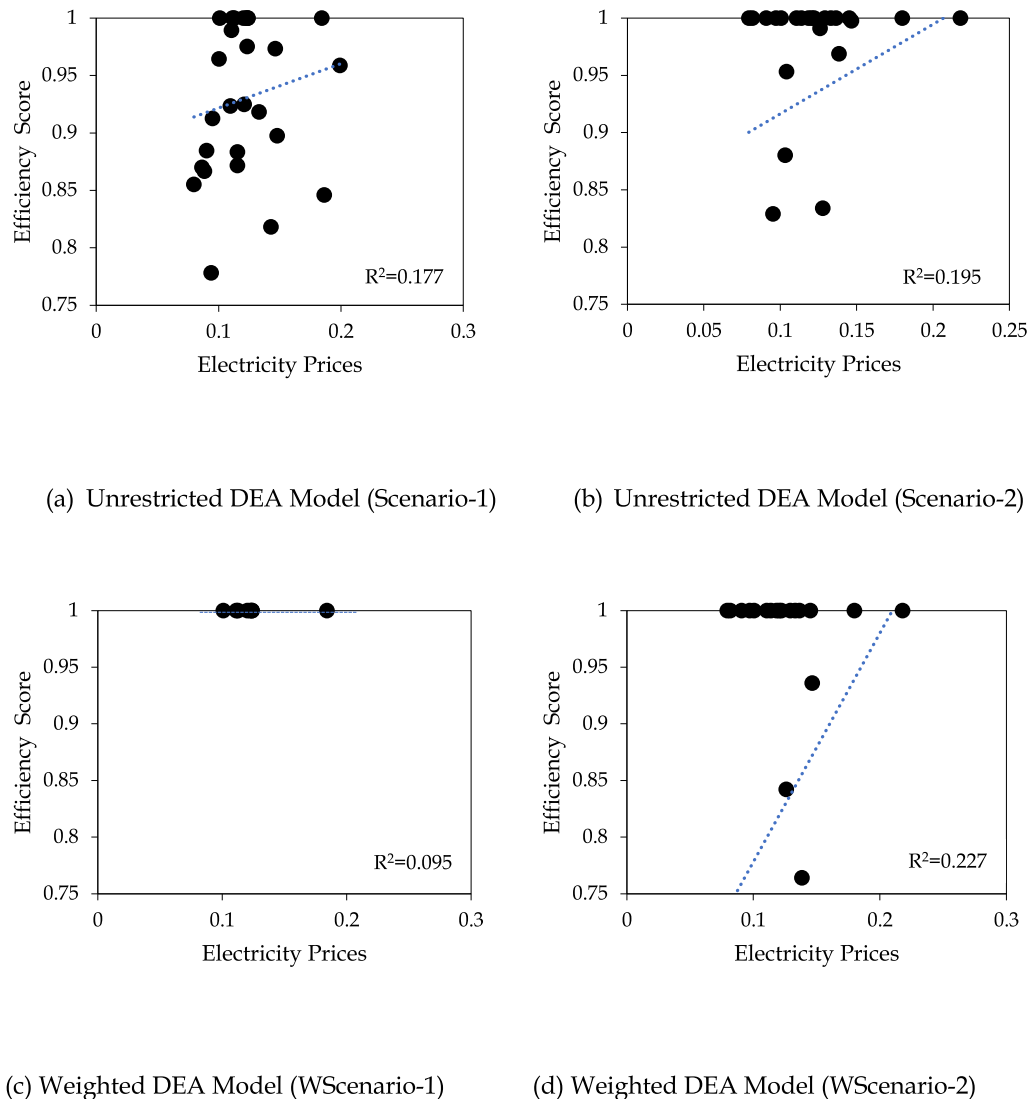


Fig. 7. Fitting plots and  $R^2$  for unrestricted and weighted DEA models a) Scenario-1 b) Scenario-2 c) WScenario-1 d) WScenario-2.

Table S4 shows the least efficient country like the Czech Republic (CZ), accounting for an  $\xi = 0.241$  under Scenario 2. Cyprus ( $v_4 = 0.918$ ) and Portugal ( $v_5 = 0.082$ ) were chosen as the reference set to guide Czech Republic (CZ) for becoming efficient unit. Similarly, while considering Scenario 3, Table S5 demonstrates that Cyprus ( $v_6 = 0.747$ ) and Slovakia ( $v_7 = 0.253$ ) were taken as the benchmarking units for the inefficient unit Lithuania (LT). The assigned weights for each reference set are multiplied with the respective environmental impact categories to lay pathways for the inefficient units to improve their performance. The average projection level for the former is 69.56%, and the latter is 4.57%. While considering Scenario 2, the Czech Republic needs to cut down the impacts by 63.24% from the climate change category, followed by 57.576% from freshwater eco-toxicity and 97.328% from freshwater eutrophication inefficient performance. While 90.227% needs to be downsized from the human toxicity impact category, 34.461% from metal depletion, 81.156% from particulate matter formation, 34.461% from photochemical oxidant formation, 84.796% from the terrestrial acidification, and 82.76% from the urban land occupation-related impacts for possible efficiency improvements. Scenario 3 projection level analysis's results indicate that Lithuania needs to decrease its share across "climate change-related impacts, freshwater

eco-toxicity, freshwater eutrophication, human toxicity, metal depletion, particulate matter formation, petrochemical oxidant formation, terrestrial acidification, and urban land occupation" value by 25.717%, 1.849%, 0.007%, 11.448%, 1.573%, 0.01%, 0.018%, 0.007%, and 0.47%, respectively. Finally, when considering all the weighted DEA Scenarios, the Czech Republic (CZ), Estonia (EE), and Hungary (HU) were found to be the inefficient and the least performing European countries under WScenario 1, WScenario 2, and WScenario 3, respectively.

Diving deep into each scenario, Table S6 shows that France with a weight of  $v_8 = 0.714$  and Sweden with an assigned weight of  $v_9 = 0.286$  need to be multiplied with their respective environmental impact categories to reach efficiency levels under WScenario 1. Similarly, Table S7 illustrates the weights assigned to Cyprus ( $v_9 = 1$ ) under WScenario 2 and, Table S8 indicates that Slovakia ( $v_{10} = 0.011$ ) and Cyprus ( $v_{11} = 0.989$ ) under WScenario 3 need to be multiplied with the respective input parameters to push the inefficient countries namely; Estonia and Hungary to fall onto the efficient frontier. The average projection levels for the Czech Republic (CZ), Estonia (EE), and Hungary (HU) are 73.63%, 75.09%, and 8.62%, respectively, for the weight-restricted condition. In the meantime, WScenario 1, WScenario 2, and



WScenario 3 are considered with their environmental indicators and provided with their overall projection levels. To improve the sustainability performance of the inefficient units, not all the inputs need to be reduced or outputs are increased. Some inputs remain constant whose increase or decrease does not affect the overall outcome.

#### 4. Conclusions and policy recommendations

This research used a WTW-LCA combined with weight restricted and unrestricted DEA to measure the environmental efficiency for each of the 27 European countries. An efficiency performance grouping scheme was then used to identify the grouped performance scores for each country. Finally, a model-based variability assessment using a non-parametric test was undertaken, supported with a projection level analysis. The projection level analysis can help the least performing countries in identifying pathways to reach the efficient frontier.

The results revealed 16 out of 27 member states are efficient under the marginal electricity mix for both the restricted and un-restricted scenarios. Only 6 countries were termed efficient under the weight-restricted renewable energy-based electricity mix (2030–40) scenario. Similarly, only 8 countries managed to make up to the efficiency frontier under the average electricity mix scenario for both the weight restricted and unrestricted model. In most scenarios, average mixes cause lower environmental efficiency scores of battery electric vehicles than marginal mixes due to higher shares of renewable electricity sources in marginal mixes. The findings also prove that the decarbonization of the power generation sector could lead to favorable environmental efficiency performance. This can be seen when considering the case of renewable energy-based electricity mix under Scenario 3. Countries showed excellent performance in terms of their use of BEVs on highways under scenario 3 for all of Europe. Scenario 3 acts as a baseline in addressing climate change-related impacts. Similar results can be seen under WScenario 3 that uses the same renewable energy-based electricity mix. All the countries fall under the fairly high-performing to the excellent-performing category in this scenario. However, countries including Romania, the Czech Republic, and Estonia should strengthen their EV usage policies for different electricity mixes. Under all the scenarios, these countries showed below-average performance. Thus, the findings in this study critically acknowledge the advantage of the use of decarbonized energy supply in the power mix to cut down emissions from all the impact categories.

National incentives and benefits apart from the central European commission incentives can strengthen the nationwide EV adoption. The monetary EV incentives in Belgium, EV registration tax benefits in Denmark, 100% exemption on ownership tax for EVs that emit less than 50g CO<sub>2</sub>/km and the attractive scrappage scheme offered by France for EVs are all examples of national incentives to strengthen the EV adoption to reach maturity. However, despite the promising benefits offered by the subsidies to commercialize the use of EVs with the meta goal of carbon emission reduction, the case of Finland is surprising and an answer to the research conducted in this study. Finland is well known for no subsidies and tax incentives when it comes to the use of EVs. However, the study Finland is the highest performing country across all the six scenarios. The reason behind the meritorious performance of Finland can be attributed to its bio-fuel adaption policy post-2015 and the switch to intense carbon neutral practices.

Furthermore, the use of differentiated smart metering systems for EV charging can help separate taxation for electricity use by EV adopters to take advantage of the government incentives for EVs. To socially optimize the use of EVs on highways, policymakers can implement charges on the number of emissions per vehicle type as the EV market transitions towards maturity. Such initiatives can open a new market to the concept of EVs for sharing economy.

Power generation from a clean energy source has become a key overlay in bringing carbon neutral and circular economy opportunities in the transportation industry. The global consensus to push for the

electrification of public transport is a positive step towards lowering emissions in cities. Electrification of public transport also provides an opportunity to achieve multiple objectives of low-carbon urban development, reduction of local air pollution, creation of jobs, and higher acceptance of public transport by residents. To be successful, electric urban buses must be approached as a coherent system that embraces the vehicle, the infrastructure, the operation, the users, and the financial sustainability. Cities can also shape the transition to electric-shared mobility by partnering on pilot programs centered around EV adoption, charging, and innovative multi-modal first/last mile programs. For future research, the authors suggest choosing the full ReCipe endpoint impact categories to understand the destructions inflicted on human health, ecosystem health, and resource damage using alternative mobility practices in Europe under the same scenarios using the environmental, social LCA approach. Furthermore, the authors suggest conducting a material footprint analysis to identify and compare the emissions associated with the materials required per unit generation of electricity utilizing the decarbonized technologies with the traditional fossil fuel generation system. A scenario-based multi-level integrated LCA approach is suggested to identify the carbon emissions associated with electricity generation technologies under energy scenarios. It is readily important to determine the actual share-of-use of low-carbon energy per km for EVs with the identified saving potential values from using “renewable electricity mix” to avoid the unfair estimation of advantage for EVs. In addition, the authors suggest the combined application of hybrid life cycle sustainability assessment and DEA models to measure the social, economic, and environmental performance for the complete electrification of passenger cars based on the triple bottom line sustainability impacts in Europe and the globe. Therefore, the authors propose to include extra environmental and socio-economic indicators such as material footprint, life cycle cost, and economic value-added and develop a holistic input-output hybrid life cycle sustainability assessment of battery electric vehicles considering the full life cycle stages, including the circular economy applications of end of life batteries.

#### CRedit authorship contribution statement

**Murat Kucukvar:** Methodology, Writing – original draft, Conceptualization, Supervision. **Nuri C. Onat:** Writing – original draft, Writing – review & editing, Visualization, Data curation. **Adeeb A. Kutty:** Methodology, Writing – original draft, Writing – review & editing. **Galal M. Abdella:** Formal analysis, Writing – original draft, Writing – review & editing. **Muhammet Enis Bulak:** Software, Formal analysis, Writing – original draft. **Fajr Ansari:** Formal analysis, Writing – original draft, Data curation. **Gurkan Kumburoglu:** Validation, Writing – review & editing.

#### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jclepro.2021.130291>.

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