QATAR UNIVERSITY

COLLEGE OF ENGINEERING

ENVIRONMENTAL EFFICIENCY OF ELECTRIC VEHICLES IN EUROPE: A WELL-TO-WHEEL LIFE CYCLE ASSESSMENT-BASED DATA ENVELOPMENT ANALYSIS

BY

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ABSTRACT

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Title: Environmental Efficiency of Electric Vehicles in Europe: a Well-to-Wheel Life Cycle Assessment-Based Data Envelopment Analysis

Supervisor of Thesis: Murat, Middle Initial, Kucukvar.

The environmental problems have raised the world demand toward a rapid change in the policy-making to achieve environmental sustainability. Nowadays, the world and especially the European countries have focused the studies and investments on the adoption of the electric vehicle as a way to reduce the effect of environmental burdens and achieve sustainability in the field of e-mobility. For this purpose, this study introduces the first empirical analysis that used Well- to- Wheel LCA method to cover the scenarios of average electricity mix, marginal electricity mix (2015-2020), and renewable energy-based electricity mix (2030-2040) to assess the efficiency of 27 European countries usage of the battery electric vehicles. In order to achieve this, the midpoint method is considered in estimating the environmental impacts of generating one kWh of electricity for each European country utilizing the latest data published by ecoinvent. Based on that, the environmental footprints produced by one kWh of electricity are estimated per country. Then, the well-to-wheel method is applied to calculate the environmental impacts of BEVs using the functional unit per km traveled. The implicit weighting of data envelopment analysis and the expert judgment-based weights that are obtained from the survey of the European Commission’s Joint Research Center (JRC) are then modeled to evaluate and compare the footprint efficiency of different electricity mix production scenarios. The results of the efficiency analysis revealed that the countries with the highest efficiency usage for all electricity

mix in unrestricted scenarios are France, Finland, and the Netherland. While most of the European countries were observed to be efficient for the renewable energy-based in the unrestricted DEA scenario. The surprising results appear when the weight restricted scenario of renewable energy-base was put under comparison with the unrestricted scenario of the same type, the result showed that 81.48% of the European countries were considered environmentally efficient for the unrestricted scenario while a drastic change to around 77% of the countries was found to be inefficient in the weight restricted scenario with a score ranging from 0.968 to 0.754. This study can present the roadmap for the policymakers towards decarbonized energy supply in the power generation mix to cut down emissions from all the environmental impact categories.

DEDICATION

This thesis is dedicated to my family and friends who have always believed in me, inspired me, and encouraged me throughout my academic journey…

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1. THESIS OVERVIEW

1.1 Introduction

Transport emissions of the European Countries account for nearly a quarter of the total greenhouse gases (GHG) emissions with an amount of 945,871.55-kilo tonnes Co_2 equivalent this can be seen in figure 1. The percentage of transport emissions including residential and commercial road transport. (EEA, 2019)

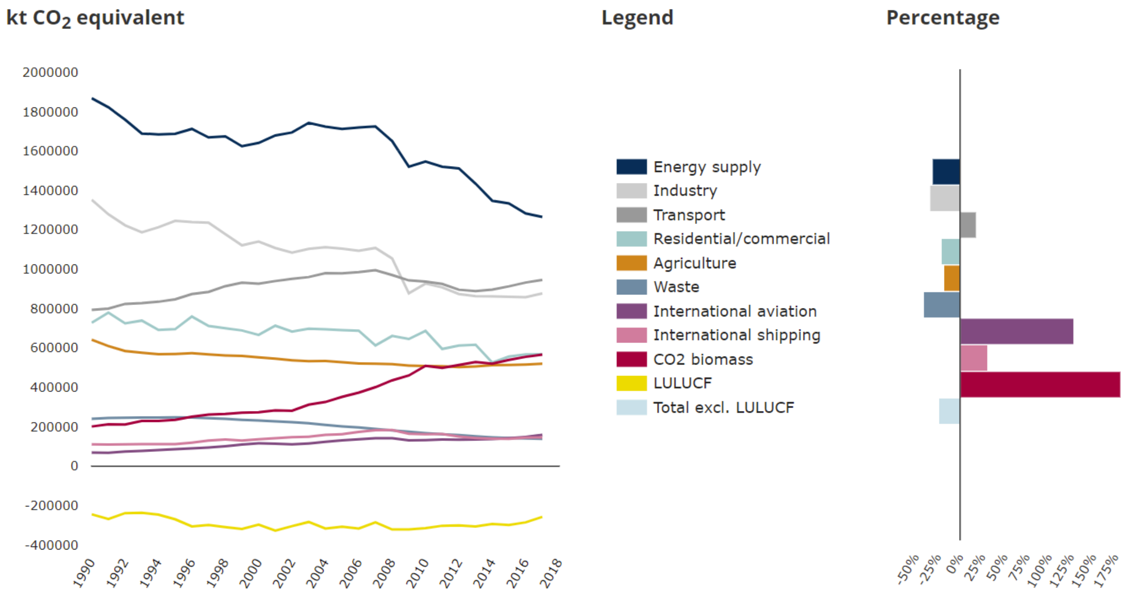


Figure 1. EU's emissions of the transport sector

For the periods between 1995 and 2019, emissions from passenger vehicle transportation have increased by 28% instead of a planned decrease of 2.5 metric tons of emissions from light-duty vehicles by 2020 (Ritchie, 2020). Experts from International Energy Agency predict an increase in the number of personal vehicle transportation as the global population increases, where the demand for car ownership would peak to a value of 63% by 2070 (Yuan et al., 2018). These numbers have pushed the use of fuel consumption patterns against the frontiers of sustainability and have left concerns in cutting down the GHG emissions to mitigate climate change-related impacts such as global warming.

The global push to halt fossil fuel dependence has left automotive manufacturers in countries including France, Germany and, the United Kingdom (UK) to purely ban vehicles powered by combustion engines by the end of 2040 (IEA, 2019). Clean electric mobility alternatives will be key to lessen the costs of climate change and create a balance between sustainable growth patterns and carbon-neutral objectives of the Paris Agreement (Biresselioglu et al., 2018; Onat et al., 2017; Liang et al., 2019). In this context, leading economies around the globe including the United States (U.S), Canada, and Europe are targeting major shares of investments to support sustainable mobility practices through the deployment of Electric Vehicles (EV) onto their highways (Onat et al., 2019). Booming economies like India and the Middle East have also taken initiatives in joining hands to support the e-mobility practices (Puertas et al., 2020).

Electrified powertrains continue to gain popularity worldwide as a dominant clean fuel alternative to the traditional “internal combustion vehicles” (ICV) (Hawkins et al., 2013; Heidrich et al., 2017). European countries have started to show some pockets of growth in the EV uptake rate since 2014, with 60% of new vehicle registrations in Norway falling in the EV category post-2018 (EEA, 2020). Europe stands as the first runner up to date in EV adoption due to the declining manufacturing costs and, nation-wide 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% to 4.2% in 2019 (IEA, 2019).

Combined EV adoption targets have been set by the European commission across each member state to reach 9-10 million EV users on road by the end of 2022 (McKinsey & Company, 2014). But within the major European countries, the timeline and targets along the road to large-scale EV adoption vary drastically across each state and from city to city (McKinsey & Company, 2014). Accordingly, the Netherlands has set an aspiring target of 1 million EV users on highways by the end of 2025. While, France has paved stones to a more ambitious target of 2 million EV users by early 2024, where Germany expects a figure of over 1.5 million EVs on road by 2025. Understanding the dynamics related to the adoption of EV across the member state is crucial in structuring policies to support the penetration of additional support infrastructures like charging service solutions to users.

The shift in the global powertrain portfolio accompanies a set of sustainability-related questions, namely 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. Consequences related to the energy storage systems, range anxieties, impact backed with the increased use of low-carbon sources in the power mix (Wolfram et al., 2018; 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. This thesis thus stays as a backbone in signaling action plans to accelerate the EU-wide large-scale EV adaption to support sustainable mobility.

Studies to date have focused on several life cycle approaches and efficiency evaluation techniques for EV sustainability assessment using non-parametric methods. This study is the first of its kind to understand 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 state used for powering the BEVs along with the energy efficiency by the use of BEVs. In addition, the panel-based weights obtained from the survey of the European Commission's Joint Research Center is used to model the environmental efficiency (Sala et al. 2018). Several controversies exist in the contingent weights assigned using the linear programming model by the DEA to the inputs and outputs. The implicit weighting using DEA and the expert judgment-based weights were used to evaluate and compare the footprint efficiency results related to different electricity production mix scenarios. This helps in understanding the change impact on each EU member state's efficiency that can rule out cognitive bias and support unbiased decision making.

1.2 Problem Statement

One of the fundamental keys that evolved human civilization and have a great impact on economic growth is energy. The huge role that energy takes place in building the current development can not be estimated or measured by a practical magnitude. Obtaining access to a sufficient amount of energy becomes a global demand toward the development of industrial, agricultural, transportation, and all aspects of modern life. This global demand has been constantly increasing over the years. In 2018 the world production rate of electricity has increased by 3.9% to reach a gross production of 26730 TWh. The shares of production for the non-renewable sources (fossil fuels) are 63.9% where the renewable sources are accounted for the rest which is 36.1% (IEA, 2018). With the majority of the world's electricity generation being sourced from non-renewable energy sources, the environmental burdens become greater. Freight and passenger road transportation is responsible for around a quarter of the global CO2 emissions. Emissions from light-duty vehicles have increased by 28% instead of a planned decrease of 2.5 metric tons of emissions from the period between 1995 and 2019 (Ritchie, 2020). Due to the increase in emissions, the fuel consumption patterns have raised an alarming need to cut down the GHG emissions to mitigate climate change-related problems. Therefore, the United States (U.S), Canada, and Europe have focused their investments and studies toward a clean alternative that achieves sustainable mobility through the utilization of electric vehicles (Onat et al., 2019).

Thus, many studies have emphasized studying the environmental impact using different methods including LCA to assess the electric vehicles from cradle to grave in order to estimate their environmental impact. This thesis sheds the light on studying well-to-wheel LCA analysis to account for all the impact of the fuel chain from production till operations, as well as the fuel consumption of the vehicle. The results of LCA analysis are then combined with weight-restricted and unrestricted DEA models to evaluate the environmental efficiency of BEV using different production electricity mix scenarios.

1.3 Objectives

Most studies of sustainability on e-mobility have not applied parametric analysis in their research. Therefore this study is considered as the first empirical analysis that focused on understanding and analyzing the interconnections between different production of electricity mix scenarios used for supplying BEVs and studying their efficiency.

On all account, this thesis aims to cover the following objectives to broaden the scope of EV environmental sustainability assessment across Europe:

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 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 in relation with the present and future electricity production mixes.

1.4 Thesis layout

This thesis consists of five chapters. Chapter one provides an overview of the thesis. The purpose of this chapter is to present the reasons for choosing this thesis topic. This chapter also underlines the complexity of the problem, problem statement, the objectives of the thesis, and the uniqueness of the methods applied in this thesis. Chapter two presents a comprehensive literature review of the methods and models used in this thesis. This chapter includes a literature review of environmental life cycle assessment models, environmental LCA of electricity production, LCA of electric vehicles, and efficiency assessment using DEA. Chapter three provides a detailed presentation on the methods used for this thesis. This chapter is highlighting the methods used in detail and how they are utilized to accomplish the purpose of this thesis. This chapter includes data collection, analysis of the data, and running the models to obtain the results. This chapter presents in detail the well-to-wheel analysis combined with weight restricted and unrestricted DEA models to assess the environmental efficiency of each of the 27 European countries towards the use of BEVs comparing three scenarios which are average electricity mix, marginal electricity mix, and renewable energy-based electricity mix. Chapter four presents the results and discussions. This chapter highlights the results of the analysis conducted for all the scenarios considered for this thesis. A comparison of the results between the weight-restricted and unrestricted DEA models. A model-based variability assessment is then conducted to determine the significant difference in the mean score across each scenario. Efficiency performance grouping is used to group the efficiency score for each DMU under their respective scenarios depending on their performance. Using projection level analysis which helps countries move towards the sustainable use of BEVs following best-performing peers. Chapter five presents conclusions and future work. In this chapter, a conclusion for all the work done on the thesis is presented as well as a roadmap to help guide futuristic policies towards net zero carbon electricity production plans.

2. LITERATURE REVIEW

2.1 Environmental life cycle assessment models

Environmental life cycle assessment (E-LCA) is an environmental management system-tool widely applied in calculating the associated environmental impacts of products, processes, and services across their life cycle (LC) (Heijungs, 1992; Bhat and Prakash, 2009; Arveseh and Hertwich, 2012). It provides a holistic view of all the potential environmental burdens that can be developed from the product's life-cycle (Friedrich and Buckley, 2002). Understanding the ecosystem-related impacts across the stages of the life cycle became an important and core element for any assessment during the early 1970s till late 1980s (Sala et al., 2018). Initially, the partial LCA approach that formed the basis of studies included limited impact categories including energy consumption and solid waste (Owens, 2000; Kucukvar and Tatari, 2012; Sen et al., 2020). Following a period of diminishing interests by the research community on partial E-LCA models during the early 1980s, compilation and assessment of environmental impacts using a comparative perspective were broadened to the creative use of E-LCA models for dynamic and nonlinear systems that include ecosystem restoration and regionalized activity-based mechanisms (Guinee et al., 2011). Life cycle studies have broadened the scope to midpoint impact categories (Vasquez-Ibarra et al., 2020). These impact categories account for the damages caused to human health, resource base deterioration, and ecological system effectiveness by the intervention of a product or service either voluntary or involuntary into the environment (Stamford and Azapagic, 2012; Asdrubali et al., 2015).

Recent noticeable contributions of the integration of new technologies with the life cycle assessment. (Zhang et al, 2020) have developed a framework that provides guidance and support to implement the methodology of blockchain-based LCA. In this study, the new technology of blockchain associated with other technology such as the internet of things, the analytics of big data, and data visualizations all these technologies have participated in overcoming the problem of reliable data collection of multiple stages of the supply chain and achieve excellence in the organizational operation due to the efficient and effective implementation of LCA that led in improvement in supply chain environmental performance. Another contribution of (Hou et al, 2020) is the development of a model using machine learning that is capable of estimating the ecotoxicity produced over the life cycle of a product. In chemicals is it difficult to estimate the characterization factors of ecotoxicity due to the complexity generated during the process of interaction and transformation of the chemicals in the environment, this has been achieved by using the model of machine learning.

Regardless of the recent developments in the LCA models, the underlying principles and the process within the scope of the assessment for any type of LCA remains unchanged. The various types of LCA methods include the E-LCA, “Social life cycle assessment (S-LCA)”, hybrid LCA, LCSA, and “Life cycle costing (LCC)”. The S-LCA approach refers to the assessment of socio-economic impacts throughout the LC stages of a good or service. The S-LCA models are widely used in quantifying the social impacts across several areas of research namely; agriculture (Prasara-A and Gheewala, 2021), chemical process industry (Tsalidis et al., 2021; Naghshineh et al., 2020), wastewater treatment (Anwar et al., 2021), pork production (Zira et al., 2020), transportation (Gompf et al., 2020), building and construction (Toosi et al., 2020), plastic packaging industry (Reinales et al., 2020) and, oil and gas industry (Hannouf et al., 2020). The input-output (IO) based LCA models combined with process-LCA within a single boundary have broadened the LCA scope to give better estimates under the hybrid-LCA framework (Martinez et al., 2018). Similar to the applications of E-LCA, the hybrid LCA has been applied across several studies in the past to: estimate the GHG mitigation potential for the urban built environment (Yu et al., 2021), compare the energy efficiency of Chinese cities (Song et al., 2015), calculate resource efficiency of dams (Martinez et al., 2018) and understand the productivity of industrial sectors (Yuan et al., 2018; Wang et al., 2019).

Unlike LCA or integrated LCA, "life cycle sustainability assessment (LCSA)" is a multi-level combination of several LC models under a unified sustainability framework that consists of guiding principles and models for specific sustainability-related challenges (Finkbeiner et al., 2010). LCSA is the future framework of LCA (Santoyo-Castelazo and Azapagic, 2014). Broadening the scope from the traditional environmental impact assessment models of LCA to a more intricate network of economic and social impact categories including human health, eco-toxicity and, cumulative resource utilization, the E-LCA models have evolved to an umbrella concept underpinning a plethora of multi-disciplinary sustainability models (Guinee et al. 2011). The transdisciplinary integration of multiple models and guiding principles into a single modeling phase has resulted in broadening the object of analysis into economy-wide, meso-level, and product-oriented levels of assessment under the LCSA framework (Hannouf and Assefa, 2018). A better understanding of the LCA models can help sustainability and environmental science in designing complete solutions to work against climate change-related problems, carbon and water footprint-related sustainability concerns, and eco-design scenarios.

2.2 Environmental LCA of electricity production

The increased emissions of CO_2 over the years had led to serious problems such as environmental degradation, resource depletion, global warming, and more other problems. The key source of global CO_2 emissions is the production of energy. Most of the energy around the world used to produce electricity and since 85% of the production is accounted for fossil fuels this leads to a fact that most carbon emissions are due to electricity production (Rahman, 2020; Outlook, 2019). (Turconi et al., 2013) have reviewed 167 cases for different technologies used to produce electricity with relation to LCA to find the data that identifying the ranges of SO_2, GHG, and NO_x emissions for each used technology. It has been found that to accurately quantify the impact of the environment for each technology, the data should be evaluated with regard to three different phases of the electricity production life cycle which are infrastructure, provisioning of fuel, and the operation of a plant. The conclusion was fossil fuels have produced most of the emissions from the operations process while biomass and nuclear power have contributed by 71%, 60% of GHGs respectively from the provisioning of fuel. Whereas renewable sources are mostly contributed to affect the environment from its infrastructure. Another study, that evaluated the GHG emissions using LCA for nine different technologies used in the power systems has been conducted by (Hondo, 2005) to understand the system characteristics with respect to global warming. Further analyses were made to understand the impact of changes in the assumptions and future technology on the environment and considering the effect of uncertainty in interpreting the results while the comparison. Moreover, many studies on renewable energy sources have been conducted to quantify their impact using LCA such as (Bhat and Prakash, 2009) have reviewed the existing data of renewable energies using LCA and compare it with the conventional method in order to support the decision of choosing the best alternative. (Asdrubali et al., 2015) have shown that the results concluded of around 100 LCA cases for different renewable energies are variable and not consistent. A harmonized methodology has been used to produce more reliable results that were used in the comparison of renewable technologies. The Comparison shows that wind power has the lowest impact on the environment while PV and wind power have the highest impact. Expanding this comparison with the conventional methods resulted in significant advantages of renewable energies. Finally, This research has shown that the PV power system can be considered a promising source for producing electricity that can save the resources used and reduce carbon emissions. In addition, the recent efficiency resulted from the development of the PV system is designed to use the maximum amount of recycled material that will lead to a reduction in GHG emissions and the amount of energy required (Sherwani and Usmani, 2010).

2.3 LCA for Electric Vehicles

The switch towards carbon-neutral mobility practices have resulted in reshaping 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 (Elhamoud 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 and 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. 2019; Kutty et al. 2020; Naranjo et al. 2021). The EV-LCA studies often branch out into two prime assessment categories namely; Fuel life cycle analysis (F-LCA) and vehicle-based LCA approach (Onat et al. 2019a). Several studies have been developed and applied in the area of EV-LCA over the years. A well-to-wheel fuel LCA analysis was carried out by Lucas et al. (2012) 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 fuel cell-powered London passenger taxis consumed less energy than 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). 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 the CO2-eq emissions up to 27.41% by the use of 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 PM2.5 and Sulfur dioxide (SO2) 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 CO2 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. All these studies play a pivotal role in structuring policies to meet air quality directives and support commitments laid to accomplish emission reduction targets.

2.4 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 (Ewertowska et al., 2016; 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 (Galan-Martin et al., 2016; Mardani et al., 2017; Yu et al., 2019; Kutty et al., 2020a). The relative efficiency for each of the comparable units, as a result of using the DEA technique, appears as a non-negative score within the range of 0 to 1 (Liu et al., 2017; Zurano-Cervello et al., 2019). The efficiency scores translate the fact that each of the 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 areas of research 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. An improved window DEA was used by Zhang et al. (2021) 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. While a game theory-based “cross-efficiency DEA model” with 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 in extending its application in addressing concerns in the transportation sector as well (Neves et al., 2020). A parallel DEA model was applied in evaluating 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 (TBL) 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 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.

3. METHODS

This study uses the Well-to-Wheel (WTW) LCA method combined with 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. This thesis makes use of the latest ecoinvent v3.7 life cycle impact database. The midpoints environmental impacts per kWh of electricity generation are then estimated for each of the 27 European countries. After estimating the per kWh environmental footprints for the electricity generation per country, the well-to-wheel environmental impacts of BEVs are calculated based on the functional unit of 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 Joint Research Center" to model the environmental efficiency (Sala et al. 2018). The footprint-based efficiency related to different electricity production mix scenarios is identified. It is then compared with the traditional input-oriented DEA model results. 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 Quintiles method to identify the grouped performance scoring for each country (see Fig 1). A model-based variability assessment using the Kruskal-Wallis H test is undertaken, supported with a projection level analysis. The following sub-sections detail the methods used in this study.

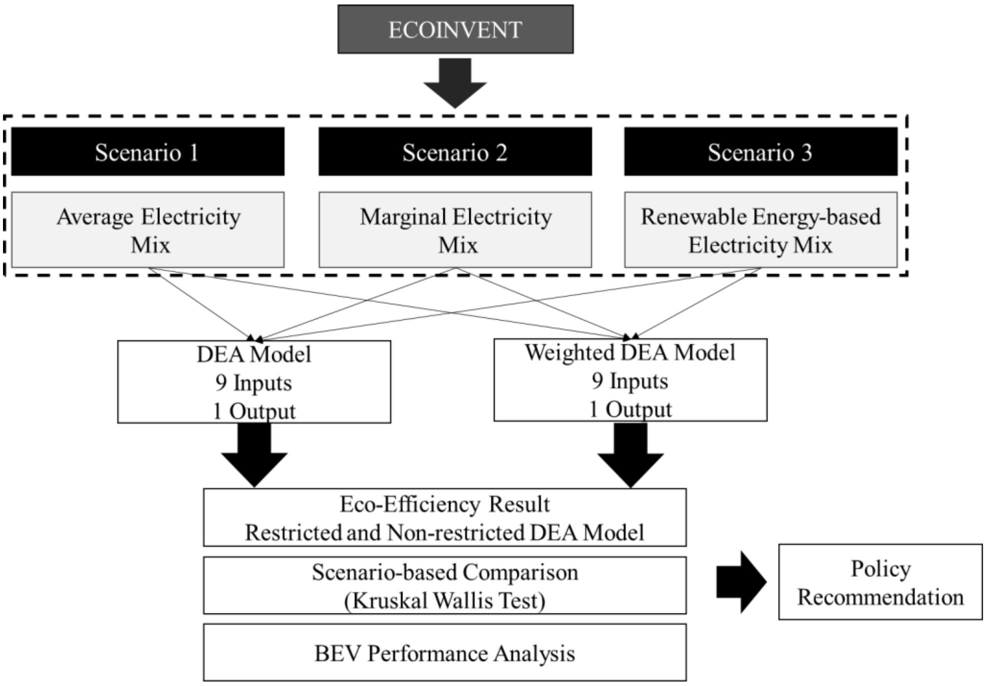


Figure 2. Thesis flow diagram

3.1 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 not only captures the tailpipe emissions but gives an entire picture of the emissions along the production, transportation, and distribution pathways of the fuel cycle. 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., 2014b). The WTW analysis can further be split into two sub-phases namely; the WTT approach and the TTW approach (see Fig. 2). The WTT analysis accounts for the indirect emissions across the entire fuel chain and not along the drive cycle. While the TTW accounts for the emissions during the driving phase of BEVs.

If *j* represents the environmental impact categories then, the associated emissions along the assessment stages for the jth category is calculated using equation(1):

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

where;

E_j = emissions associated with all the assessment stages for the jth category of environmental impact

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

WTT_j = energy consumption for the jt^h impact category associated with the electricity generation phase

TTWj = energy consumption for the j^{th} impact category across the drive cycle

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

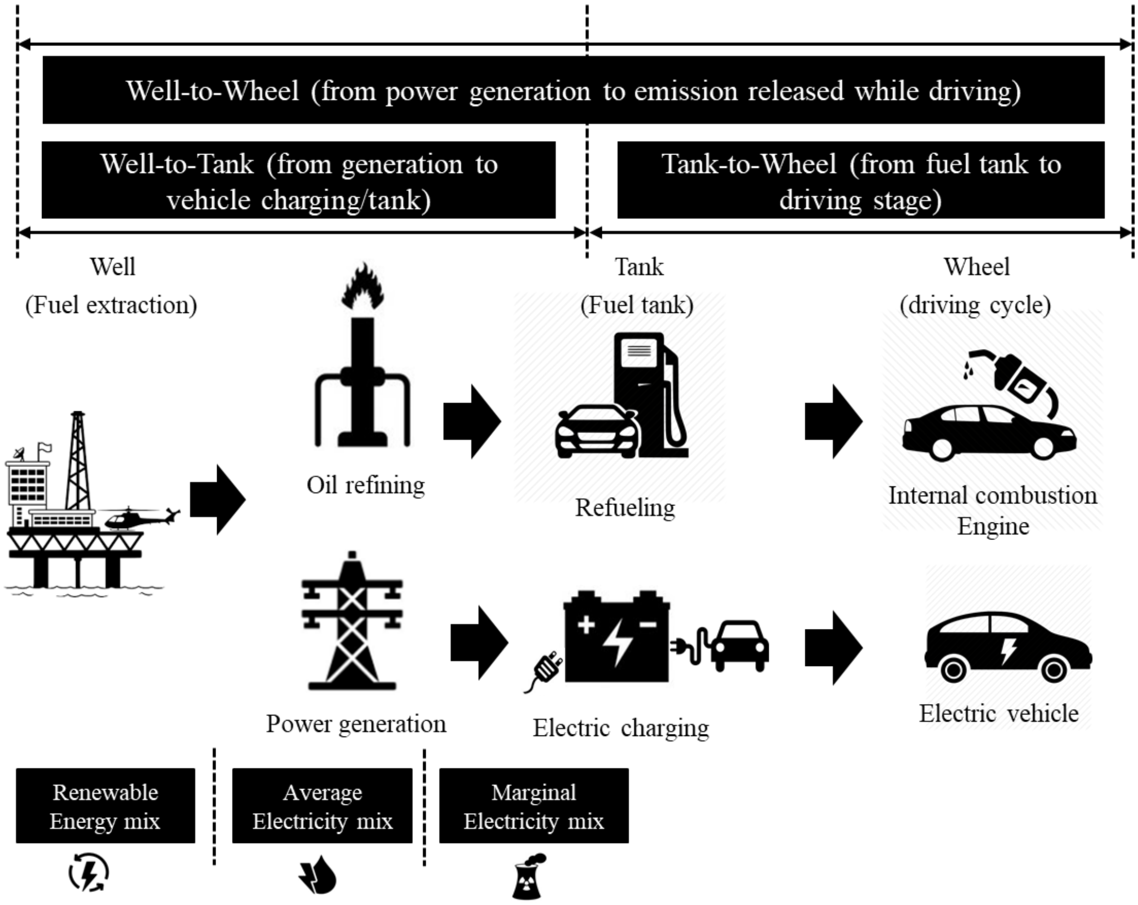


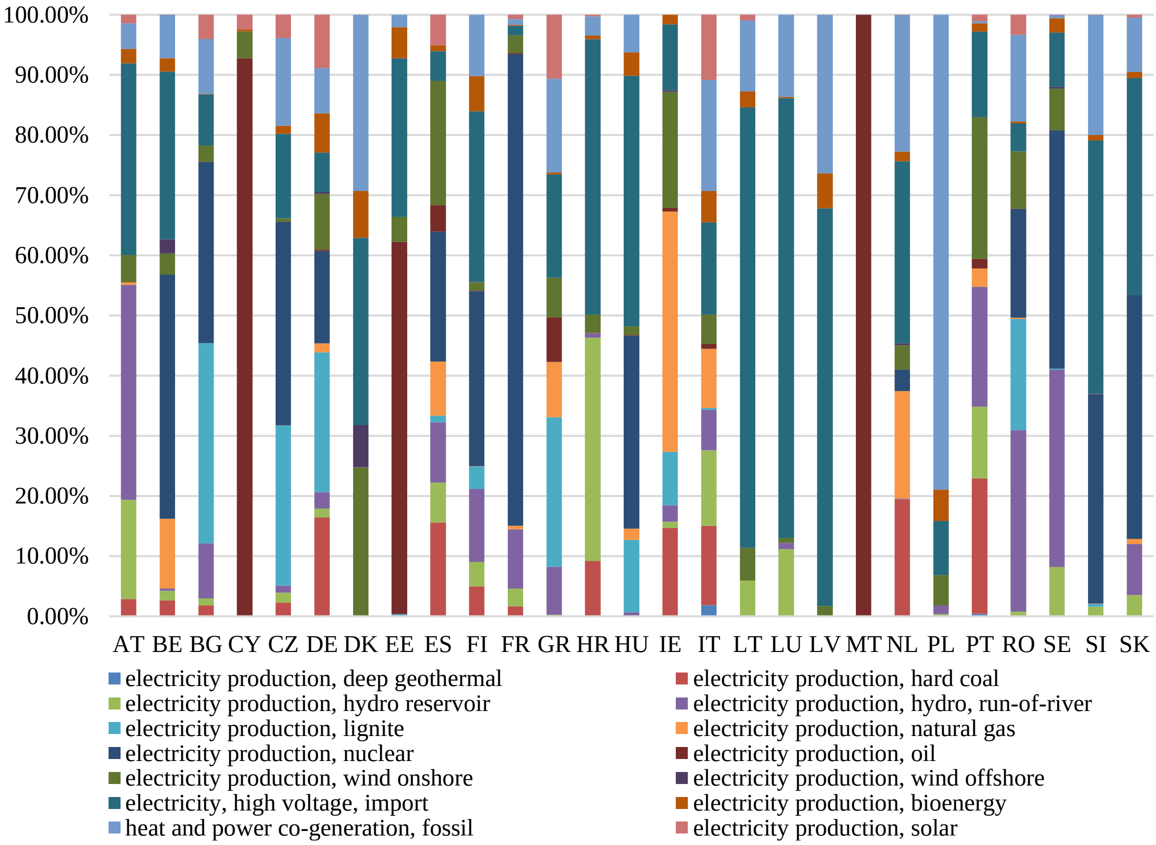
Figure 3. Schematics for a WTW analysis

The associated environmental impacts vary based on the power generation, trends in driving patterns, and weather-related uncertainties (Alghoul et al., 2018). The upstream and downstream energy consumption-related impacts vary based on the source used for the power generation (Kucukvar et al. 2018; 2017). The data for the electricity generation mix was collected from the ecoinvent v3.7 life cycle impact database for the 27 European countries across three periods: a) average electricity mix (2015), b) marginal electricity mix (between 2015 and 2020), and c) renewable energy-based electricity mix (between 2030 and 2040) (Fig. 3). As observed from (Fig. 3) scenario a, that the three main sources of energy that dominate the average electricity mix in 2015 are high voltage- import, nuclear, and heat - power co-generation-fossil respectively. The three leading countries for generating electricity using the source of high voltage- imports are Lithuania 73.18%, Luxembourg 73.07%, and Latvia 66.11%. While France, Belgium, and Slovakia are the highest scored countries using the nuclear source of energy with percentages of 78.45%, 40.59%, and 40.55%. For heat-power co-generation-fossil source of energy, Poland, Denmark, and Latvia are the most European countries that using this type of energy with percentages of 78.95%, 29.31%, and 26.38%.

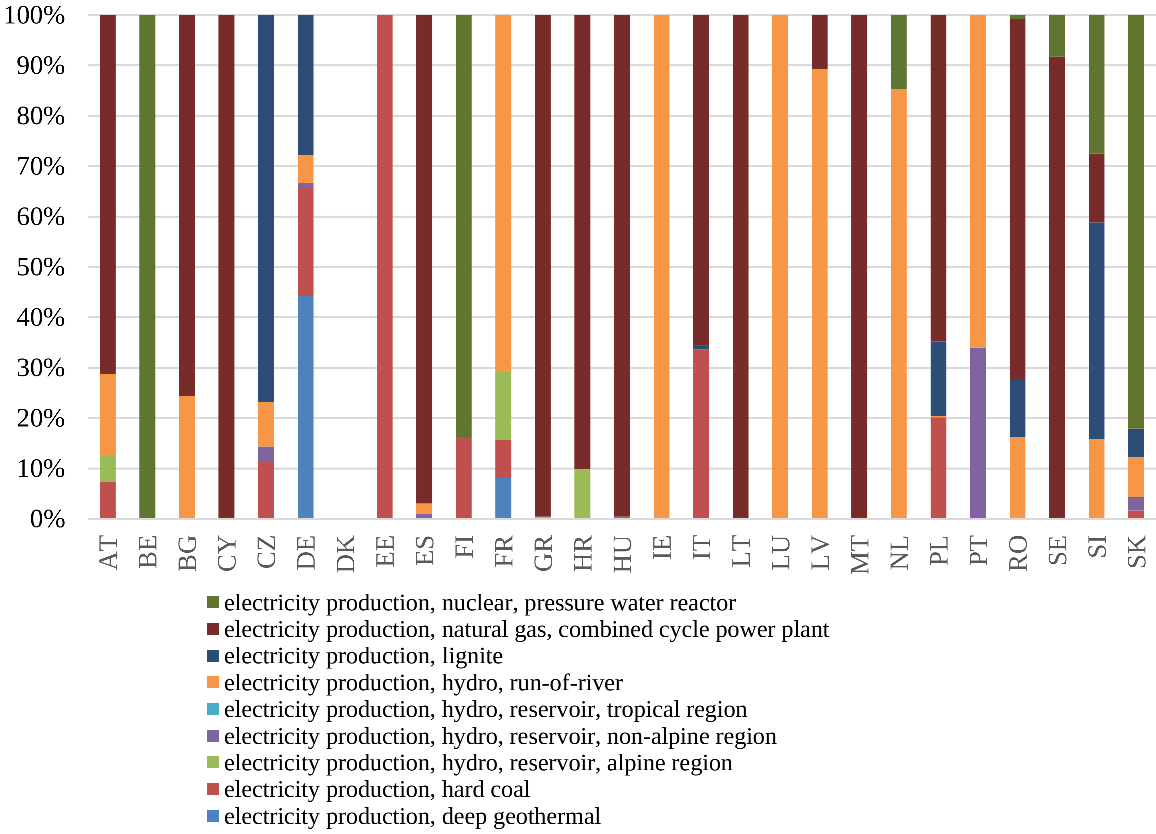
For (Fig. 3) scenario b, natural gas- combined cycle power plant, wind >3MW turbine, and photovoltaic- 3kWp slanted-roof installation -multi-Si- panel- mounted are the most used source of energy to produce the marginal electricity mix for the periods between 2015 and 2020. Where deep geothermal, hydro- reservoir- alpine region, and oil are the least used sources of energy for producing marginal electricity mix. The largest country producer of the marginal electricity mix using the energy source of wind across other types of energy sources is Irland with a production percent of 94.61%, while Lithuania is the second producer using the source of natural gas with a percent of 93.25%.

In the last scenario c (Fig. 3), the highest source of the renewable energy-based electricity mix in the period between 2030 and 2040 are photovoltaic-3kWp slanted-roof installation - multi-Si -panel- mounted, natural gas- combined cycle power plant, and wood. The leading countries using the photovoltaic source are Malta with a 98.18% production rate, Spain with 78.10%, and Portugal with 76.83%. While natural gas is most used by Luxembourg, Croatia, and Cyprus with production rates of 38.25%, 38%, and 33.51% respectively. For wood renewable energy-based the most used countries will be Latvia 16.9%, Ireland 16.32%, and Italy 13.63%. The largest producer of electricity among the European countries using the source of photovoltaic as a renewable energy source is Malta with a 98.18% production rate.

(a



b)



c)

Figure 4. a) Average b) Marginal c) Renewable energy-based electricity mix data for 27 European countries (Data source: ecoinvent v3.7)

Table 1 shows the average impact factors per kWh electricity generation by a source according to the LC analysis data collected from the latest ecoinvent v3.7. The environmental impacts of per kWh electricity generation including 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 value for the electricity consumption of the selected BEV is 0.187 kWh/km. Considering the values for the average electricity mix, marginal electricity mix, renewable energy-based electricity mix, and the associated impact categories mentioned in Table 1-3, the WTT impacts were calculated using equation (2);

$$WTT_{jk} = P_{sk} \times E_{js} \tag{2}$$

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 sources

The water consumption (L/kWh) and GHG emissions (g/kWh) values are found to be zero due to no direct emissions in the TTW stage. The environmental impact categories including climate change (kg CO2-Eq/kWh), freshwater ecotoxicity (kg 1,4-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 PM10-Eq/kWh), photochemical oxidant formation (kg NMVOC/kWh), terrestrial acidification (kg SO2-Eq/kWh), and urban land occupation (square meter-year/ kWh).

Table 1. Environmental impact data per kWh average electricity generation (source: ecoinvent v3.7)

Impact Categories		Climate Change	Freshwater Ecotoxicity	Freshwater Eutrophication	Human toxicity	Metal depletion	Particulate matter formation	Petrochemical oxidant formation	Terrestrial acidification	Urban land occupation
Weighting factors*		21.06	1.92	2.80	2.13	7.55	8.96	4.78	6.20	7.94
Countries	Code									
Austria	AT	3.27E-01	2.28E-02	3.87E-04	2.83E-01	1.18E-02	3.29E-04	5.03E-04	1.30E-03	1.76E-03
Belgium	BE	2.43E-01	1.80E-02	7.14E-05	1.08E-01	1.28E-02	2.06E-04	3.73E-04	6.37E-04	1.36E-03
Bulgaria	BG	6.84E-01	3.90E-02	1.40E-03	8.89E-01	1.39E-02	1.43E-03	1.33E-03	3.71E-03	1.92E-03
Cyprus	CY	1.05E+00	1.82E-02	4.00E-05	1.34E-01	1.43E-02	2.23E-03	4.26E-03	7.97E-03	1.96E-03
Czech Republic	CZ	7.87E-01	3.58E-02	1.24E-03	8.00E-01	1.31E-02	8.09E-04	1.45E-03	2.81E-03	2.65E-03
Germany	DE	6.20E-01	3.03E-02	8.32E-04	5.44E-01	1.44E-02	4.94E-04	6.13E-04	2.31E-03	3.57E-03
Denmark	DK	4.02E-01	2.16E-02	2.16E-04	2.16E-01	1.44E-02	3.58E-04	5.76E-04	1.38E-03	4.75E-03
Estonia	EE	9.59E-01	1.94E-02	5.96E-05	1.83E-01	1.50E-02	2.00E-03	3.86E-03	6.99E-03	3.58E-03
Spain	ES	3.69E-01	2.08E-02	1.43E-04	1.50E-01	1.48E-02	9.29E-04	1.31E-03	2.60E-03	3.43E-03
Finland	FI	2.47E-01	1.80E-02	8.48E-05	1.35E-01	1.19E-02	3.06E-04	4.61E-04	8.18E-04	2.70E-03
France	FR	5.68E-02	1.77E-02	3.38E-05	8.16E-02	1.35E-02	1.38E-04	1.56E-04	3.10E-04	6.17E-04
Greece	GR	9.07E-01	5.47E-02	2.43E-03	1.53E+00	1.40E-02	2.10E-03	1.55E-03	4.94E-03	2.03E-03
Croatia	HR	4.49E-01	2.65E-02	5.90E-04	4.12E-01	1.22E-02	1.30E-03	1.30E-03	4.18E-03	2.28E-03
Hungary	HU	5.05E-01	2.87E-02	7.39E-04	5.36E-01	1.33E-02	7.21E-04	1.12E-03	2.27E-03	2.71E-03
Ireland	IE	6.06E-01	1.98E-02	1.20E-04	1.33E-01	1.25E-02	6.18E-04	1.02E-03	2.16E-03	3.28E-03
Italy	IT	4.15E-01	1.96E-02	1.26E-04	1.32E-01	1.39E-02	6.97E-04	9.03E-04	2.82E-03	4.70E-03
Lithuania	LT	7.45E-01	2.03E-02	1.53E-04	1.81E-01	1.59E-02	1.11E-03	1.73E-03	2.76E-03	2.98E-03
Luxembourg	LU	5.65E-01	2.60E-02	6.38E-04	4.26E-01	1.28E-02	4.12E-04	5.69E-04	1.86E-03	2.12E-03
Latvia	LV	8.01E-01	1.92E-02	1.09E-04	1.78E-01	1.43E-02	1.48E-03	2.48E-03	4.78E-03	3.08E-03
Malta	MT	1.37E+00	1.90E-02	4.63E-05	1.62E-01	1.53E-02	2.89E-03	5.58E-03	1.03E-02	2.34E-03
Netherlands	NL	6.20E-01	2.09E-02	2.65E-04	2.12E-01	1.14E-02	3.02E-04	6.51E-04	1.13E-03	2.79E-03
Poland	PL	1.06E+00	3.67E-02	1.28E-03	8.61E-01	1.20E-02	1.63E-03	2.18E-03	5.74E-03	5.45E-03
Portugal	PT	4.13E-01	2.04E-02	1.49E-04	1.46E-01	1.37E-02	8.17E-04	1.28E-03	2.86E-03	3.84E-03
Romania	RO	4.87E-01	3.39E-02	9.67E-04	6.28E-01	1.54E-02	1.61E-03	1.01E-03	2.63E-03	1.45E-03
Sweden	SE	4.34E-02	1.76E-02	3.59E-05	8.22E-02	1.20E-02	1.01E-04	1.34E-04	2.30E-04	1.04E-03
Slovenia	SI	4.58E-01	2.90E-02	8.07E-04	5.43E-01	1.22E-02	1.64E-03	1.50E-03	6.56E-03	1.48E-03
Slovakia	SK	4.61E-01	2.62E-02	6.45E-04	4.56E-01	1.21E-02	8.39E-04	1.03E-03	2.67E-03	1.90E-03

* Panel-based weights assigned by the European Commission's Joint Research Centre (JRC Technical Reports, 2018)

Table 2. Environmental impact data per kWh renewable energy-based electricity generation (source: ecoinvent v3.7)

Countries	Code	Environmental Impact Categories								
		Climate Change	Freshwater ecotoxicity	Freshwater eutrophication	Human toxicity	Metal depletion	Particulate matter formation	Petrochemical oxidant formation	Terrestrial acidification	Urban land occupation
Austria	AT	2.00E-01	2.74E-02	9.88E-05	2.10E-01	3.73E-02	2.17E-04	5.25E-04	1.26E-04	1.72E-03
Belgium	BE	2.07E-01	2.89E-02	1.07E-04	1.99E-01	4.03E-02	1.98E-04	4.43E-04	-5.15E-06	1.33E-03
Bulgaria	BG	1.69E-01	2.53E-02	8.52E-05	1.83E-01	3.19E-02	1.76E-04	4.10E-04	8.48E-05	1.48E-03
Cyprus	CY	1.77E-01	2.21E-02	6.52E-05	1.27E-01	2.43E-02	1.25E-04	2.96E-04	6.44E-05	6.65E-04
Czech Republic	CZ	1.22E-01	2.75E-02	1.03E-04	2.07E-01	3.87E-02	1.87E-04	3.79E-04	-3.22E-05	1.41E-03
Germany	DE	1.86E-01	2.81E-02	1.02E-04	2.08E-01	3.83E-02	2.06E-04	4.73E-04	6.87E-05	1.63E-03
Denmark	DK	1.78E-01	2.63E-02	8.71E-05	1.63E-01	3.35E-02	1.61E-04	3.36E-04	2.33E-05	1.03E-03
Estonia	EE	1.52E-01	2.80E-02	9.18E-05	1.73E-01	3.63E-02	1.59E-04	3.21E-04	-1.61E-05	1.12E-03
Spain	ES	1.26E-01	2.77E-02	9.10E-05	1.72E-01	3.41E-02	1.71E-04	3.54E-04	4.36E-05	1.14E-03
Finland	FI	6.94E-02	2.46E-02	8.49E-05	2.00E-01	3.20E-02	1.70E-04	3.48E-04	5.58E-05	1.68E-03
France	FR	1.86E-01	2.75E-02	9.34E-05	1.79E-01	3.59E-02	1.78E-04	3.91E-04	2.76E-05	1.24E-03
Greece	GR	9.20E-02	2.97E-02	9.37E-05	1.80E-01	3.60E-02	1.54E-04	2.98E-04	-2.18E-05	1.20E-03
Croatia	HR	4.00E-01	2.72E-02	7.56E-05	1.64E-01	3.00E-02	3.43E-04	6.75E-04	8.47E-04	1.40E-03
Hungary	HU	2.52E-01	2.68E-02	8.94E-05	1.72E-01	3.47E-02	2.08E-04	5.28E-04	1.75E-04	1.17E-03
Ireland	IE	7.46E-02	2.91E-02	9.53E-05	2.32E-01	3.65E-02	1.97E-04	4.21E-04	1.11E-04	2.21E-03
Italy	IT	1.60E-01	2.51E-02	8.52E-05	2.03E-01	3.22E-02	1.97E-04	4.73E-04	1.56E-04	1.87E-03
Lithuania	LT	2.01E-01	2.70E-02	9.97E-05	2.13E-01	3.70E-02	2.00E-04	4.64E-04	3.98E-05	1.75E-03
Luxembourg	LU	2.12E-01	2.37E-02	8.01E-05	1.47E-01	3.00E-02	1.54E-04	3.63E-04	3.38E-05	8.94E-04
Latvia	LV	1.42E-01	2.48E-02	8.79E-05	2.19E-01	3.26E-02	2.03E-04	4.83E-04	1.52E-04	2.14E-03
Malta	MT	9.35E-02	2.83E-02	1.12E-04	2.07E-01	4.03E-02	1.71E-04	3.40E-04	-1.36E-04	1.35E-03
Netherlands	NL	2.13E-01	2.62E-02	9.61E-05	1.84E-01	3.54E-02	1.87E-04	4.33E-04	3.25E-05	1.30E-03
Poland	PL	1.05E-01	2.74E-02	9.42E-05	1.87E-01	3.59E-02	1.65E-04	3.18E-04	-2.61E-05	1.24E-03
Portugal	PT	7.09E-02	3.23E-02	9.67E-05	1.95E-01	3.79E-02	1.59E-04	2.93E-04	-6.32E-06	1.42E-03
Romania	RO	1.68E-01	2.84E-02	9.47E-05	2.05E-01	3.60E-02	1.94E-04	4.40E-04	8.97E-05	1.70E-03
Sweden	SE	8.29E-02	2.69E-02	9.86E-05	1.98E-01	3.71E-02	1.69E-04	3.14E-04	-5.92E-05	1.30E-03
Slovenia	SI	1.58E-01	2.40E-02	8.23E-05	1.93E-01	3.07E-02	1.84E-04	4.38E-04	1.27E-04	1.75E-03
Slovakia	SK	6.89E-02	2.44E-02	8.44E-05	1.72E-01	3.19E-02	1.46E-04	2.64E-04	-3.43E-05	1.10E-03

Table 3. Environmental impact data per kWh marginal energy-based electricity generation (source: ecoinvent v3.7)

Countries	Code	Environmental Impact Categories								
		Climate Change	Freshwater ecotoxicity	Freshwater eutrophication	Human toxicity	Metal depletion	Particulate matter formation	Petrochemical oxidant formation	Terrestrial acidification	Urban land occupation
Austria	AT	4.07E-01	1.93E-02	4.78E-05	1.10E-01	1.87E-02	2.06E-04	6.23E-04	5.36E-04	1.30E-03
Belgium	BE	6.82E-02	2.82E-02	6.00E-05	1.26E-01	2.84E-02	1.73E-04	2.40E-04	3.69E-04	7.15E-04
Bulgaria	BG	3.14E-01	1.96E-02	3.82E-05	1.08E-01	1.77E-02	1.56E-04	4.48E-04	3.60E-04	1.05E-03
Cyprus	CY	3.34E-01	2.06E-02	3.94E-05	9.36E-02	1.70E-02	1.23E-04	3.87E-04	2.70E-04	4.02E-04
Czech Republic	CZ	8.67E-01	4.81E-02	1.49E-03	9.58E-01	2.57E-02	8.29E-04	1.58E-03	2.71E-03	2.44E-03
Germany	DE	8.21E-02	4.45E-02	1.26E-04	2.10E-01	4.72E-02	1.51E-04	2.32E-04	2.68E-05	1.31E-03
Denmark	DK	4.25E-02	2.41E-02	5.82E-05	3.22E-01	2.68E-02	2.86E-04	7.38E-04	7.15E-04	4.80E-03
Estonia	EE	1.14E+00	3.29E-02	4.61E-04	4.07E-01	2.51E-02	2.46E-03	3.79E-03	8.25E-03	9.86E-03
Spain	ES	1.56E-01	3.05E-02	7.49E-05	1.78E-01	3.30E-02	1.56E-04	3.67E-04	1.49E-04	1.54E-03
Finland	FI	1.75E-01	2.37E-02	9.73E-05	1.36E-01	2.09E-02	1.82E-04	2.23E-04	4.50E-04	1.66E-03
France	FR	6.86E-02	3.62E-02	9.29E-05	1.94E-01	4.04E-02	1.48E-04	2.77E-04	3.55E-05	1.45E-03
Greece	GR	4.50E-01	2.38E-02	5.55E-05	1.17E-01	2.54E-02	2.91E-04	7.58E-04	7.89E-04	8.11E-04
Croatia	HR	3.97E-01	2.70E-02	7.03E-05	1.61E-01	2.99E-02	3.23E-04	6.65E-04	8.24E-04	1.37E-03
Hungary	HU	6.22E-01	1.92E-02	3.81E-05	8.59E-02	2.08E-02	2.83E-04	9.66E-04	8.15E-04	6.67E-04
Ireland	IE	3.40E-02	4.49E-02	7.77E-05	1.56E-01	3.87E-02	1.15E-04	1.19E-04	1.26E-04	1.01E-03
Italy	IT	6.22E-01	2.06E-02	1.77E-04	1.99E-01	1.98E-02	7.37E-04	1.25E-03	2.08E-03	3.68E-03
Lithuania	LT	4.59E-01	1.74E-02	3.34E-05	9.05E-02	1.56E-02	1.44E-04	4.64E-04	3.09E-04	8.28E-04
Luxembourg	LU	5.07E-02	5.37E-02	9.66E-05	2.02E-01	4.88E-02	1.67E-04	2.10E-04	2.06E-04	1.54E-03
Latvia	LV	5.43E-02	4.21E-02	7.71E-05	2.06E-01	3.83E-02	1.74E-04	3.00E-04	2.91E-04	2.06E-03
Malta	MT	3.89E-01	1.92E-02	4.23E-05	8.29E-02	1.88E-02	1.41E-04	4.40E-04	2.71E-04	4.74E-04
Netherlands	NL	5.13E-02	3.35E-02	7.74E-05	2.26E-01	3.61E-02	1.84E-04	3.87E-04	2.68E-04	2.42E-03
Poland	PL	5.51E-01	2.91E-02	5.04E-04	4.15E-01	2.02E-02	1.94E-03	1.41E-03	2.56E-03	2.96E-03
Portugal	PT	1.41E-01	1.83E-02	4.27E-05	9.46E-02	1.51E-02	5.27E-04	5.97E-04	2.02E-03	6.21E-04
Romania	RO	4.60E-01	2.45E-02	4.05E-04	3.14E-01	1.72E-02	3.80E-04	6.74E-04	1.15E-03	1.04E-03
Sweden	SE	1.36E-01	3.34E-02	6.42E-05	2.08E-01	3.09E-02	1.91E-04	4.33E-04	3.89E-04	2.39E-03
Slovenia	SI	3.69E-01	3.79E-02	7.26E-04	5.73E-01	2.72E-02	1.53E-03	1.47E-03	6.06E-03	2.00E-03
Slovakia	SK	1.03E-01	1.98E-02	1.95E-04	2.21E-01	1.63E-02	7.46E-04	3.88E-04	7.01E-04	1.27E-03

3.2 Data Envelopment Analysis for efficiency assessment

DEA approach compares each DMU only with the best set of DMUs for relative efficiency calculation. While these DMUs are determined as the best form of the efficiency limit, the efficiency of any DMU is measured based on this limit. This method considers the best DMUs as relatively efficient on the efficiency limit and these units are referred to as reference sets (Thanassoulis et al., 2004). Other DMUs that are not located on the efficiency limit are considered relatively inefficient units.

DEA guides managers and decision-makers in improving the effectiveness of relatively inefficient decision-making units regarding inputs and outputs (Zhao et al., 2018). Several different measurement units are used simultaneously for input and output variables (such as weight, number, monetary or proportional size) for the analysis. DEA constitutes the theoretical background of this study. Models that are provided with this methodology allow you to compute "Total efficiency", "Technical efficiency" and "Scale efficiency" values. Using the system-related input combination in producing as many outputs as possible is defined as "technical efficiency", at an appropriate scale in production is defined as "scale efficiency". Besides, a multiplication of “technical efficiency” and “scale efficiency” yields the “total efficiency” (Cazals et al., 2002).

In DEA, efficiency measurement is made under the assumption that the production function (also called production limit, efficiency limit) is known and the efficiency of the systems is measured relative to the production limit (Mavi and Mavi, 2021). Also, the degree to which the output amount of a system is below the production limit concerning the input is defined as its relative inefficiency (inefficiency) measure. Therefore, the production limit should be determined correctly to reach the correct results. (Banker et al. 1984; Kucukvar et al., 2020).

3.3 Input-oriented DEA model

There are mainly two different models that form the infrastructure of DEA methodology. A “constant-return to-scale” model developed by Cooper, Charnes, and Rhodes (1978) and a “variable return-to-scale” model developed by Banker, Charnes, and Cooper (1984). This study uses the input-oriented CCR model due to the robust efficiency measures delivered by the model under realistic scenarios (Ozden, 2008; Lombardi et al., 2019; Supciller & Bulak, 2020).

Another issue in DEA is the choice of either the “input-oriented (IO)” or “output-oriented (OO)” DEA approach. In the IO method, the minimum amount of input (input minimization) to be used to produce a given output is considered. In the output-oriented perspective, the maximum amount of output (output maximization) to be produced with a given input is taken as a basis. Considering these two optimization problems that are dual of each other gives the same effective limit, but sometimes differences may occur in inefficient units. The study aims to cut down the environmental impacts under the triple bottom line umbrella for the member states to be efficient in terms of their use of EVs. For this reason, the first model which is the IO DEA multiplier model was used.

Eq.3 represent x_j and y_k as the jth input and kth output for the respective DMU under evaluation. To estimate the relative efficiency, we use the ratio between the weighted output (WO) with respect to the weighted input (WI) as represented in (Eq.4) (Onat et al. 2017 a,b):

$$\mathrm{WI} = \sum_{j=1}^{\mathrm{p}} v_j\, x_j \qquad ; \qquad \mathrm{WO} = \sum_{k=1}^{\mathrm{q}} \mu_k\, y_k \tag{3}$$

Where;

P = number of input DMUs

q = number of output DMUs

$v_j \geq 0$ = weights assigned to the jth input

$\mu_k \geq 0$ = weights assigned to the kth output

The environmental efficiency can be computed using equation (4);

$$\xi = \frac{\mathrm{WO}}{\mathrm{WI}} = \frac{\sum_{k=1}^{q} \mu_k y_k}{\sum_{j=1}^{p} v_j x_j} \tag{4}$$

The DMU's weights, v_j and μ_k are arbitrarily chosen by linear programming. The proposed DEA model is as follows;

Objective Function

$$\max z = \sum_{k=1}^{q} \mu_k y_k \,/\, \sum_{j=1}^{p} v_j x_j \tag{5}$$

Subject to;

$$\max z = \sum_{k=1}^{q} \mu_k y_k / \sum_{j=1}^{p} v_j x_j \leq 1, j = 1, \ldots, N \tag{6}$$

$$\mu_k, v_j \geq 0 \tag{7}$$

Where;

x_{ij} and y_{ki} = jth input and kth output of the ith DMU,

Z = total number of DMUs.

Increasing the input variables or reducing the output variables is crucial in obtaining the anticipated efficiency level (Park et al. 2015). This model can be interpreted as the following: DMU$_j$ *is* considered efficient if the value of the objective function z (Eq. 5) is 1that are subjected to constraints (Eq. 6 & 7). If the value is found to be less than 1, the DMU$_j$ is considered inefficient where the inputs of DMU$_j$ were not able to reach a sufficient level producing the output for other DMUs.

3.4 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 the use of different input and output weights of different DMU, thus eliminating the need to obtain a common weight set for all decision-making units.

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 (Podinovski and Thanassoulis, 2007; Gumus et al., 2016; 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 (Kuosmanen, 2005; Tatari and Kucukvar, 2012; 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. 5) is converted into a mathematical programming model by multiplying the inverse function of the environmental efficiency ratio to form (Eq. 8), subject to the constraints (Eq. 9) and (Eq. 10).

$$\min z^{-1} = \frac{1}{Y_j} \sum_{i=1}^{m} v_i x_{ij} \quad (8)$$

Subject to

$$\frac{1}{Y_j} \times \sum_{i=1}^{m} v_i\, x_{ij} \geq 1, j = 1, \dots, N \quad (9)$$

$$v_r \geq 0 \quad (10)$$

Y_j is the per km traveled by the DMU_j. This model does not require any multipliers due to the existence of a single output. The weight restricted model (Eq. 11) helps us in identifying whether discrimination limits the capacity of the DEA model to bring efficient results when 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 (12), (13), (14), and (15). This model reads as follows:

$$\min z^{-1} = \frac{1}{Y_j} \times \sum_{i=1}^{m} v_i x_{ij} \quad (11)$$

Subject to

$$\frac{1}{Y_j} \times \sum_{i=1}^{m} v_i\, x_{ij} \geq 1, j = 1, \dots, N \quad (12)$$

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

$$\beta_j v_1 - v_j \leq 0, j = 2,3, \dots, s \quad (14)$$

$$v_r \geq 0 \quad (15)$$

where αj and βj = positive scalars. Weights gathered from the European Commission’s Joint Research Center (Sala et al. 2018) is used to denote the constraint (Eq. 16) given as follows:

$$V_{climatechange} \geq V_{particulatematterformation} \geq V_{urbanlandoccupation} \geq V_{metaldepletion} \geq V_{terrestrialacidification} \geq V_{petrochemicaloxidantformation} \geq V_{freshwatereutrophication} \geq V_{humantoxicity} \geq V_{freshwaterecotoxicity} \quad (16)$$

The weights are assigned to each of the midpoint impact categories using an equal weighting approach by the expert panel. The experts use 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 model. Assigning weights by the experts to the impact categories can have great significance on the efficiency outcomes for each DMU. Table 4 shows all the six DEA models categorized into weighted and non-weighted scenarios along with the inputs and outputs. All the inputs listed in Table 4 fall under the environmental impact categories while per km travel is used as the output indicator. Under the proposed framework, three different analyses were carried out for both the weighted and non-weighted scenarios using an input-oriented DEA model.

Table 4. Proposed Scenarios with Inputs and Output of the DEA Model

Scenario with Energy Source	Inputs	Unit	Output
Scenario-1: Average electricity mix (2015)	Climate change	kg CO_2-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_2-Eq/ kWh	
	Urban land occupation	square meter-year/ kWh	

4. RESULTS AND DISCUSSIONS

4.1 Unrestricted DEA Model

This section attempts to explain the analysis conducted for all six scenarios. (Fig.4) shows the relative environmental efficiency score (ξ) under all the Scenarios (Scenario 1, Scenario 2, Scenario 3) for each of the European member states. The results appear as a non-negative score within the range from 0 to 1. Each of the 27 European countries is ranked in the ascending order of their performance under Scenario 1 as shown in (Fig.4). The results reveal Romania with an environmental efficiency score of ξ = 0.7781 as the least performing European country relative to other comparable units.

On the other hand, European countries like Slovenia, Sweden, Netherlands, Great Britain, France, Finland, Belgium and, Austria were ranked among the top with an efficiency score ξ = 1. When, Netherlands, France, Finland, and Belgium retained their position under Scenario 2 (Fig. 4) as the most environmentally efficient countries in terms of their use of EVs, Slovenia, Sweden, 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 ξ = 0.6554. Romania, the least performing country in terms of its relative efficiency under scenario 1 showed considerable improvement under scenario 2 (ξ = 0.9531). Despite the improvement, Romania still falls under the “fairly good” performing category in the medium efficiency zone. Under this scenario, apart from the aforementioned countries, Slovakia, Portugal, Malta, Latvia, Lithuania, Italy, Ireland, Hungary, Denmark, Cyprus, and Bulgaria were termed environmentally efficient with an efficiency score ξ=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 ξ =1. It is under Scenario 3, that most of all the European countries showed meritorious performance in comparison with the least performing countries. The least performing countries under scenario 3 do hold a fairly high-efficiency score (ξ=0.999) compared to the least performing countries in Scenario 1 and Scenario 2.

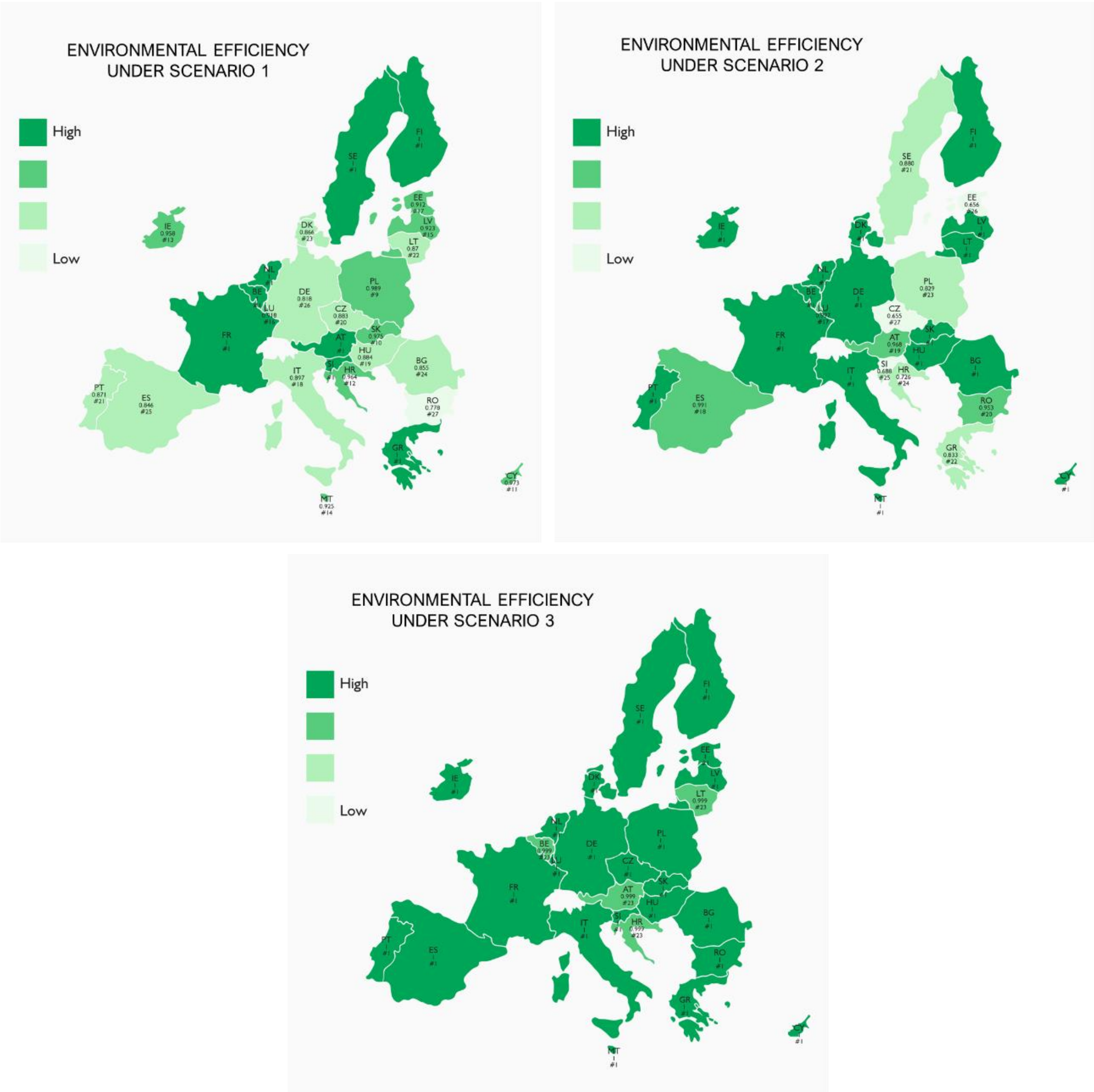


Figure 5. Environmental efficiency and ranking results of BEVs under nonrestricted model

4.2 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 5 shows the results under the weight-restricted DEA model for WScenario 1, Wscenario 2, and Wscenario 3. The countries that were categorized as the most efficiently performing units under Scenario 1 for the non-weighted DEA model (Fig 4) when 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 the 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 ξ score equal to 0.8834. An efficiency score of 0.8834 is fairly good in comparison with the Wsecanrio 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. 5), we can see that all the efficient countries under WScenario 2 (Fig. 6) remained the same as Scenario 2, like the former case mentioned. While, Estonia with an efficiency score $\xi = 0.248$ is the least efficient country in terms of their use of 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, Czech Republic and, Cyprus as the environmentally efficient country in terms of 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.

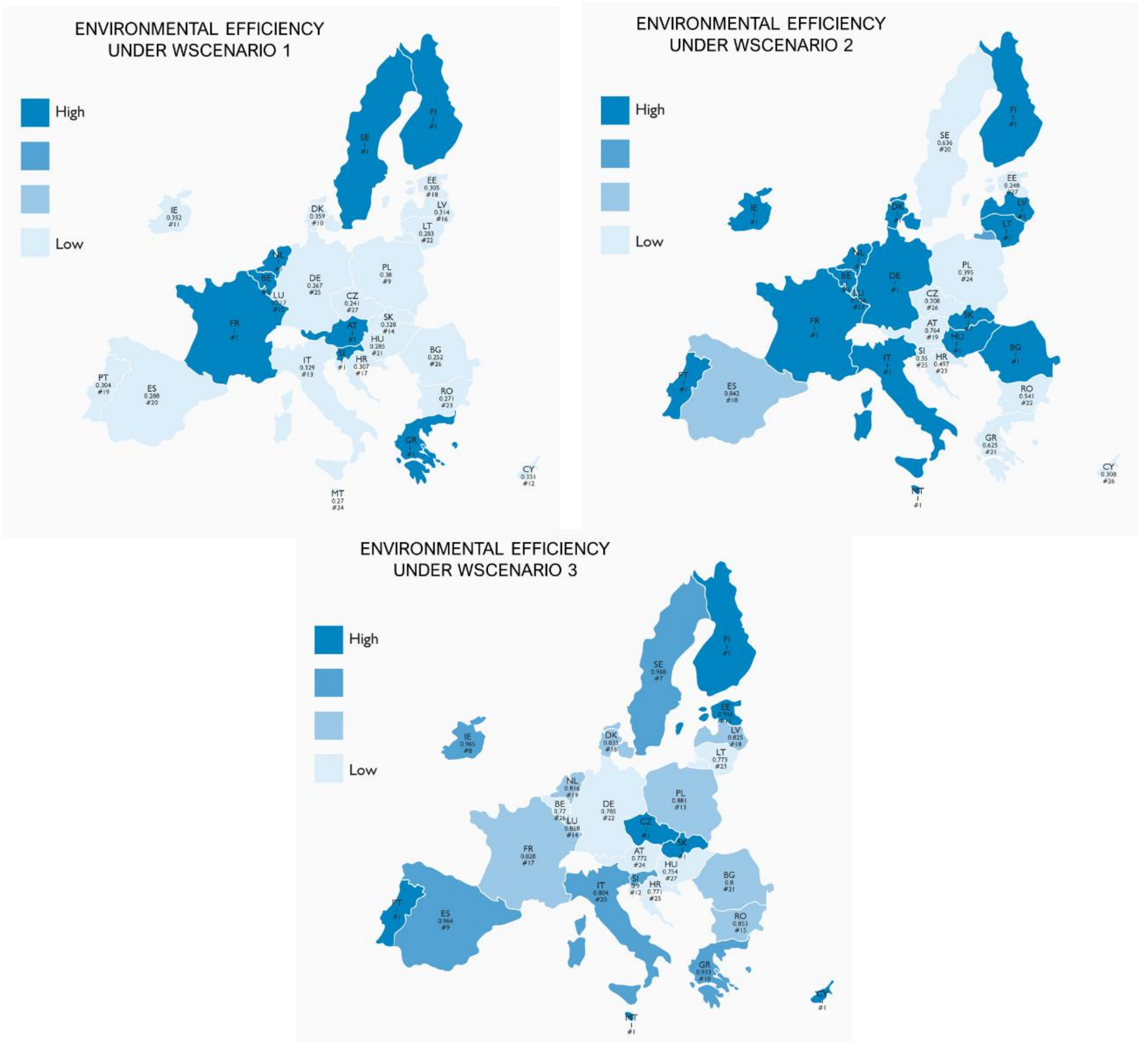


Figure 6. Environmental efficiency and ranking results of BEVs under the weight restricted model

4.3 Model-based variability assessment

A non-parametric test to determine the significant difference in the mean ξ score across each scenario is conducted using the Kruskal-Wallis H test. 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 ξ score is equally distributed to the alternative hypothesis (H_A) that there exists at least one ξ score significantly different from the overall sample. The test hypothesis can be represented as; $H_0 = \mu_{\xi(1)} = \mu_{\xi(2)} = \ldots.. = \mu_{\xi(6)}$ and $H_A = \mu_{\xi(1)} = \mu_{\xi(2)} \neq \mu_{\xi(3)} = \ldots.. = \mu_{\xi(6)}$; where $\mu_{\xi(j)}$ is the mean ξ score for the j^{th} Scenario. The Kruskal-Wallis H test statistics can be calculated using equation(17);

$$H = \frac{\sum_{\text{all } j} \left(\overline{X}_j - \overline{X}\right) (Z-1)}{\sum_{\text{all } j} \sum_{k=1}^{n_j} \left(X_{jk} - \overline{X}\right)^2}; \qquad \text{For } j = 1,2,\ldots,6 \tag{17}$$

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

$\overline{X}_j$ = average rank for the j^{th} Scenario

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

To determine whether the mean ξ score across each scenario varies significantly from each other, a 95% significance level represented by $\alpha = 0.05$ is chosen to compare the estimates with the p-value. If p-value $>$ α, the H statistics is insignificant. Thus, we fail to reject H_0. This translates to the fact that the mean ξ score across each scenario is insignificantly different from the other. On the contrary, if the p-value $\leq \alpha$, there is sufficient evidence to prove that the mean ξ score across each varies significantly from the other. 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, we conclude the fact that either of the scenarios dominates the other, resulting in rejecting the null hypothesis. The influence of input and output variables on the mean ξ score can be studied using pairwise comparison. The pairwise comparison aims to identify the set of scenarios with similar ξ scores. The combination for each scenario can be calculated using equation (18);

$$C_r^n = \frac{n!}{(n\text{-}r)!\ r!}; \qquad \text{For } n = 6 \text{ and } r = 2 \tag{18}$$

where;

n = number of scenarios

r = number of subsets under comparison

Table 5 shows the pairwise comparison results of ξ score for a significance level of α = 0.05. Based on the results of the pairwise comparison, we can see that there assumes an insignificant difference in the mean ξ 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 ξ score across Scenario 1 with Scenario 3 and Wscenario 1. Similarly, the pairwise comparison results show a significant difference when compared across Scenario 2, Scenario 3, and Wscenario 1.

Table 5. Pairwise comparison on the mean ξ 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		√

Analysis Category	Kruskal-Wallis	P-value	Decision	
			Insignificant	Significant
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		√
WScenario1 Vs.WScenario2	39.352	0.014		√
WScenario1 Vs.WScenario3	22.019	0.967	√	
WScenario2 Vs.WScenario3	17.333	1.000	√	

4.4 Efficiency performance grouping

The efficiency scores for each DMU under the respective scenario were grouped depending on their performance. One of the most common methods customarily used in the grouping is the Quintiles (Q) method. The method divides the data set into five equal intervals. These interval groups are tagged “Poor”, “Slightly Fair”, “Fair”, “Good” and “Excellent”. Performance grouping helps in understanding the impact of having certain output parameters in the production set on the total efficiency performance. Once the data set is divided into five equal intervals, each DMU is placed in the appropriate quintile based on their efficiency scores to better understand the standing of each DMU relative to one another. (Fig.6) 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 gradience for each quintile. The results 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. It was found that all the countries that fell under the "Good performance" quintile in Scenario 1 were pushed to the poorly performing category under WScenario 1. All the countries under Scenario 3 except Austria, Belgium, Hungary, and Latvia maintained an "Excellent performance". Estonia and Croatia were grouped as the least performing countries across all the six scenarios followed by Austria, Czech Republic, Poland, and Romania.

EU Countries	**Scenario 1**	**Scenario 2**	**Scenario 3**	**WScenario 1**	**WScenario 2**	**WScenario 3**
AT	5	4	4	5	3	3
BE	5	5	4	5	5	3
BG	4	5	5	1	5	4
CY	4	5	5	1	5	5
CZ	4	3	5	1	1	5
DE	4	5	4	1	5	3
DK	4	5	5	1	5	4
EE	4	3	5	1	1	4
ES	4	4	5	1	4	4
FI	5	5	5	5	5	5
FR	5	5	5	5	5	4
GR	5	4	5	5	3	4
HR	4	3	5	1	2	3
HU	4	5	4	1	5	3
IE	4	5	5	1	5	4
IT	4	5	5	1	5	4
LT	4	5	4	1	5	3
LU	4	4	5	1	4	4
LV	4	5	5	1	5	4
MT	4	5	5	1	5	5
NL	5	5	5	5	5	4
PL	4	4	5	1	1	4
PT	4	5	5	1	5	5
RO	3	4	5	1	2	4
SE	5	4	5	5	3	4
SI	5	3	5	5	1	4
SK	4	5	5	1	5	5

Color Code Key				
Poor	Slightly Fair	Fair	Good	Excellent

Figure 7. Comparative performance assessment

4.5 Projection Level Analysis

This section attempts to carry out a projection level analysis for all the six scenarios discussed in this thesis. The percentage reduction level corresponding to each environmental impact category help in understanding 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 to move towards the sustainable use of BEVs following its best-performing peers. Table 6 shows the reference set and average projection level for Romania (RO) under Scenario 1. Romania with an efficiency score of $\xi = 0.7781$ is observed to be the least efficient European country in comparison with other counties. 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 of the benchmarked units need to be multiplied by their corresponding weights for Romania to be considered efficient. Figure 7 depicts the projection levels considering environmental impact categories of each country for all six scenario analyses. 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 as seen in (Fig.7a).

Table 7 shows the least efficient country like the Czech Republic (CZ) that accounts for an $\xi = 0.241$ under Scenario 2. Cyprus (v4 = 0.918) and Portugal (v5 = 0.082) were chosen as the reference set to guide Czech Republic (CZ) for becoming efficient unit.

Similarly, while considering Scenario 3, Table 8 demonstrates that Cyprus (v6 = 0.747) and Slovakia (v7 = 0.253) were taken as the benchmarking units for the inefficient unit Lithuania (LT). The assigned weights for each of the reference set is 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, 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 to improve the 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 as indicated in (Fig 7b). Scenario 3 projection level is illustrated by (Fig. 7c) which indicates 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, 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 of the scenarios Table 9 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 10 illustrates the weights assigned to Cyprus (v_9 = 1) under WScenario 2 and, Table 11 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, Wscenario1, Wscenario 2, and Wscenario 3 are taken into consideration with their environmental indicators and provided with their overall projection levels as illustrated in (Fig. 7d-f.) It is to be noted that 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.

Table 6. Benchmark levels for Romania (RO) in Scenario 1

Inputs	Romania Best Level	Reference Set	Average Projection Level (%)
Climate change	0.01446	Austria (AT), Netherland (NL), Sweden (SE)	61.33
Freshwater ecotoxicity	0.00338		
Freshwater eutrophication	1.4E-05		
Human toxicity	0.01936		
Metal depletion	0.00224		
Particulate matter formation	2.3E-05		
Photochemical oxidant formation	0.00019		
Terrestrial acidification	6.5E-05		
Urban land occupation	0.00021		

Table 7. Benchmark levels for the Czech Republic (CZ) in Scenario 2

Inputs	Czech Republic Best Level	Reference Set	Average Projection Level (%)
Climate change	0.0594	Cyprus (CY), Portugal (PT)	69.56
Freshwater ecotoxicity	0.0038		
Freshwater eutrophication	7.4E-06		
Human toxicity	0.01746		
Metal depletion	0.00314		
Particulate matter formation	2.9E-05		
Photochemical oxidant formation	4.7E-05		
Terrestrial acidification	7.7E-05		
Urban land occupation	7.8E-05		

Table 8. Benchmark levels for Lithuania (LT) in Scenario 3

Inputs	Lithuania Best Level	Reference Set	Average Projection Level (%)
Climate change	0.02784	Cyprus (CY) Slovakia (SK)	4.57
Freshwater ecotoxicity	0.04252		
Freshwater eutrophication	0.08172		
Human toxicity	0.10746		
Metal depletion	0.12576		
Particulate matter formation	0.12785		
Photochemical oxidant formation	0.12793		
Terrestrial acidification	0.00098		
Urban land occupation	0.03844		

Table 9. Benchmark levels for Czech Republic (CZ) in Wscenario 1

Inputs	Czech Republic Best Level	Reference Set	Average Projection Level (%)
Climate change	0.00987	France (FR) Sweden (SE)	73.63
Freshwater ecotoxicity	0.00329		
Freshwater eutrophication	6.4E-06		
Human toxicity	0.01525		
Metal depletion	0.00245		
Particulate matter formation	2.4E-05		
Photochemical oxidant formation	0.00012		
Terrestrial acidification	5.4E-05		
Urban land occupation	0.00014		

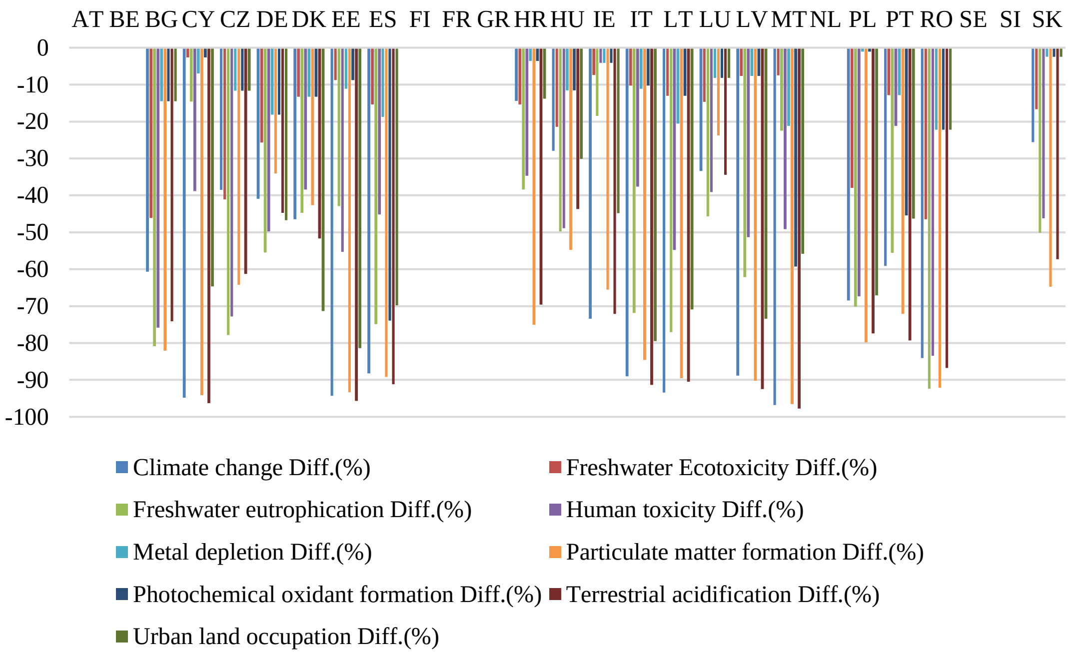
Table 10. Benchmark levels for Estonia (EE) in Wscenario 2

Inputs	Estonia Best Level	Reference Set	Average Projection Level (%)
Climate change	0.06234	Cyprus (CR)	75.09
Freshwater ecotoxicity	0.00384		
Freshwater eutrophication	7.3E-06		
Human toxicity	0.01744		
Metal depletion	0.00317		
Particulate matter formation	2.3E-05		
Photochemical oxidant formation	2.8E-05		
Terrestrial acidification	5E-05		
Urban land occupation	7.5E-05		

Table 11. Benchmark levels for Hungary (HU) in Wscenario 3

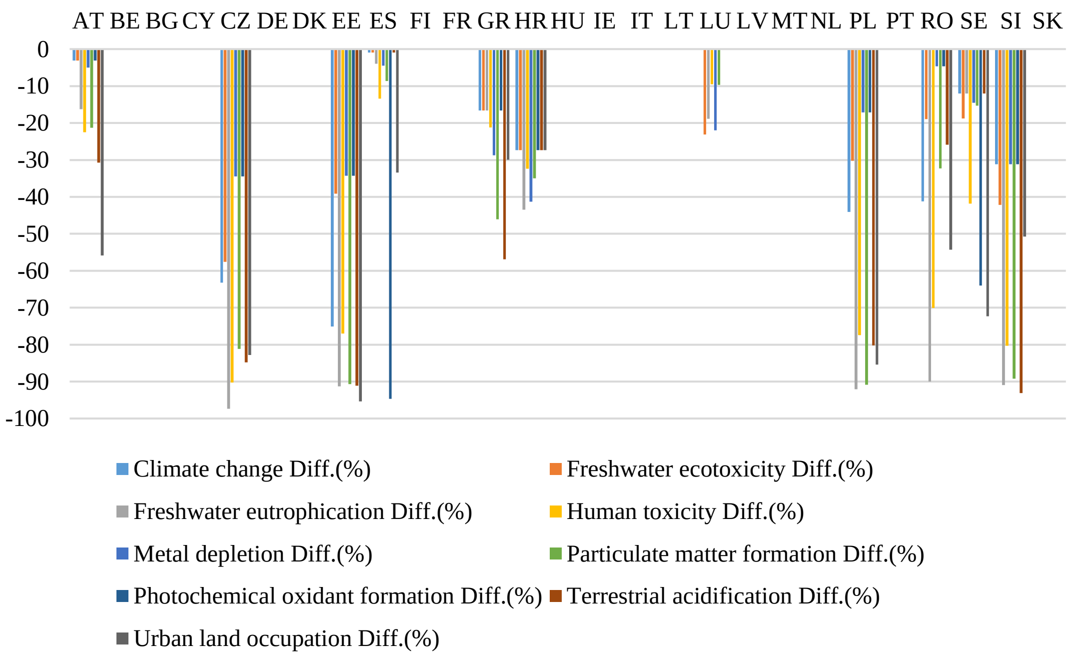
Inputs	Hungary Best Level	Reference Set	Average Projection Level (%)
Climate change	0.01307	Cyprus (CR), Slovakia (SK)	8.62
Freshwater ecotoxicity	0.04283		
Freshwater eutrophication	0.08172		
Human toxicity	0.11373		
Metal depletion	0.12679		
Particulate matter formation	0.12785		
Photochemical oxidant formation	0.12795		
Terrestrial acidification	0.00097		
Urban land occupation	0.0385		

a)



AT BE BG CY CZ DE DK EE ES FI FR GR HR HU IE IT LT LU LV MT NL PL PT RO SE SI SK
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-100
Climate change Diff.(%)
Freshwater Ecotoxicity Diff.(%)
Freshwater eutrophication Diff.(%)
Human toxicity Diff.(%)
Metal depletion Diff.(%)
Particulate matter formation Diff.(%)
Photochemical oxidant formation Diff.(%)
Terrestrial acidification Diff.(%)
Urban land occupation Diff.(%)

b)



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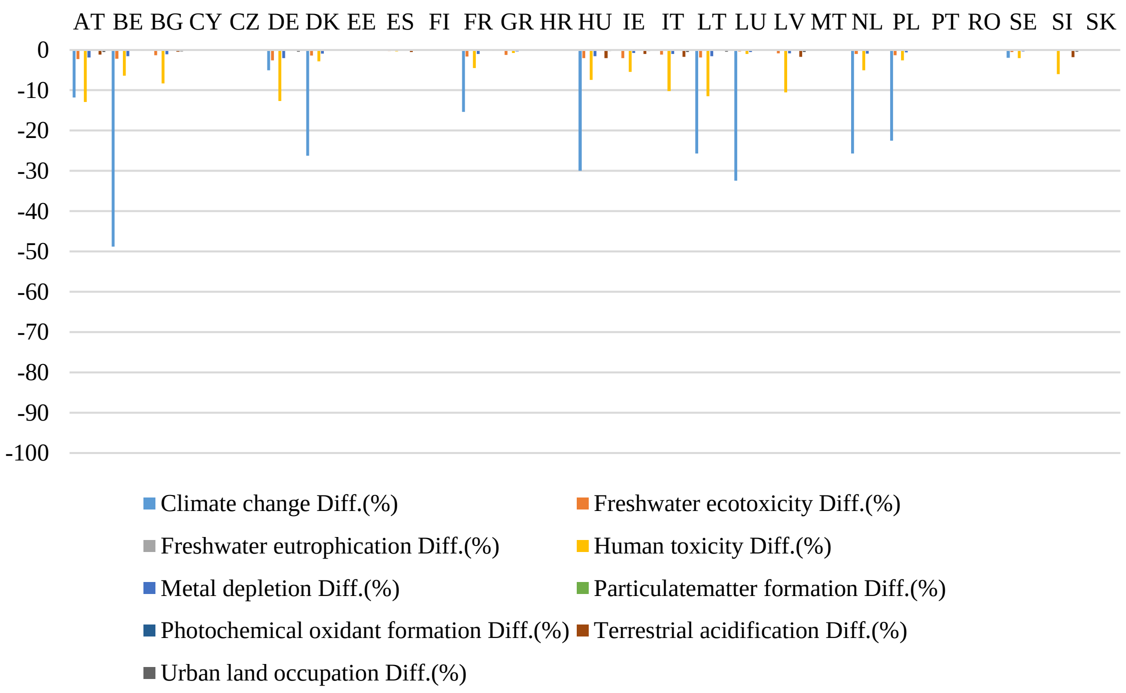
Climate change Diff.(%)
Freshwater ecotoxicity Diff.(%)
Freshwater eutrophication Diff.(%)
Human toxicity Diff.(%)
Metal depletion Diff.(%)
Particulate matter formation Diff.(%)
Photochemical oxidant formation Diff.(%)
Terrestrial acidification Diff.(%)
Urban land occupation Diff.(%)

c)



AT BE BG CY CZ DE DK EE ES FI FR GR HR HU IE IT LT LU LV MT NL PL PT RO SE SI SK
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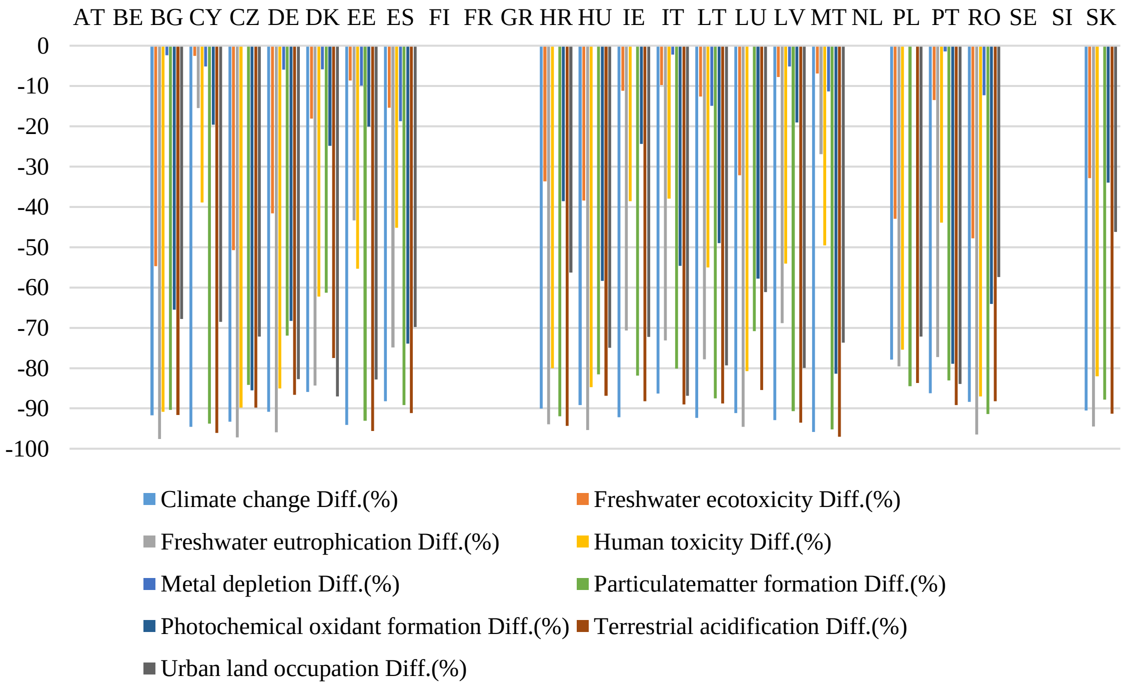
-80
-90
-100
Climate change Diff.(%)
Freshwater ecotoxicity Diff.(%)
Freshwater eutrophication Diff.(%)
Human toxicity Diff.(%)
Metal depletion Diff.(%)
Particulatematter formation Diff.(%)
Photochemical oxidant formation Diff.(%)
Terrestrial acidification Diff.(%)
Urban land occupation Diff.(%)

d)



AT BE BG CY CZ DE DK EE ES FI FR GR HR HU IE IT LT LU LV MT NL PL PT RO SE SI SK
0
-10
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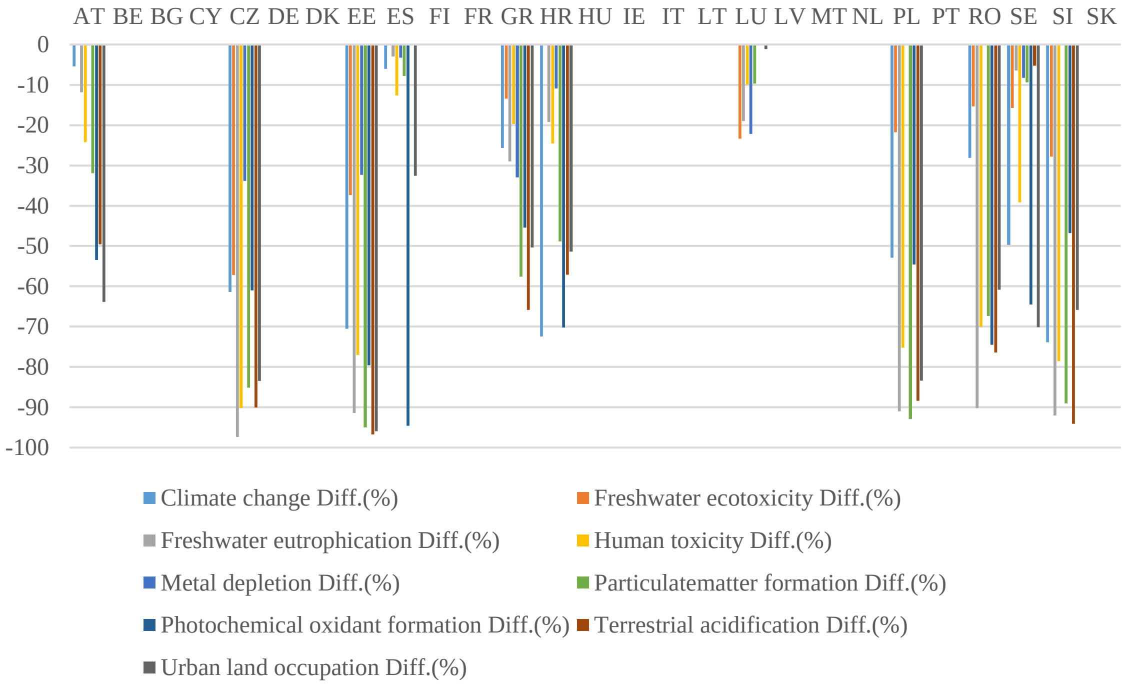
-70
-80
-90
-100
Climate change Diff.(%)
Freshwater ecotoxicity Diff.(%)
Freshwater eutrophication Diff.(%)
Human toxicity Diff.(%)
Metal depletion Diff.(%)
Particulatematter formation Diff.(%)
Photochemical oxidant formation Diff.(%)
Terrestrial acidification Diff.(%)
Urban land occupation Diff.(%)

e)



f)

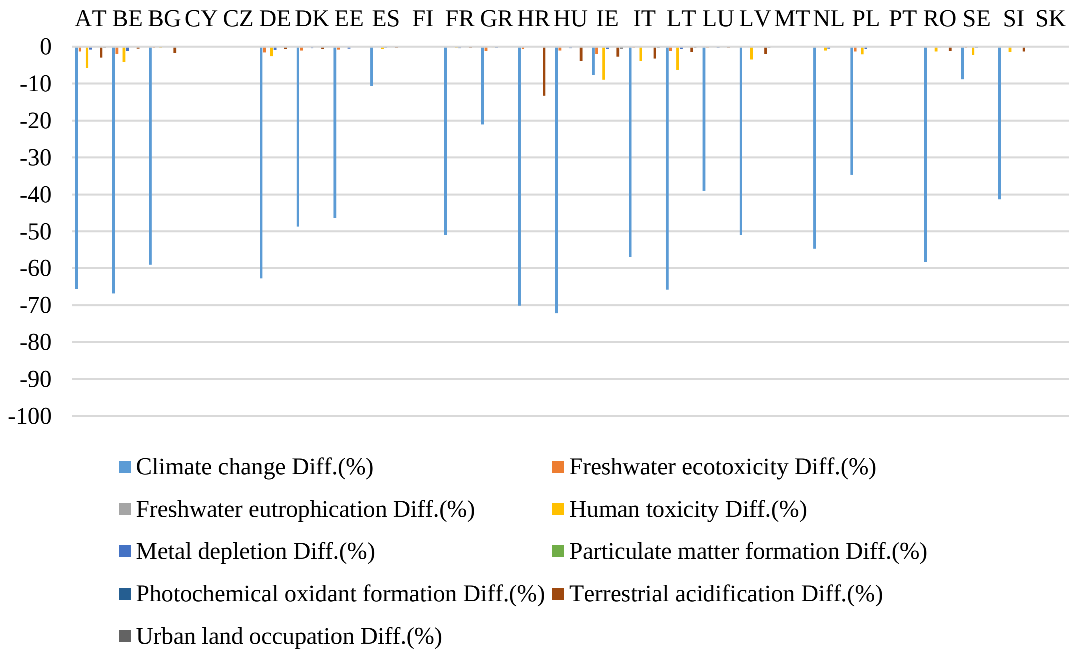


Figure 8. Projection results on environmental impact categories a) Scenario 1 b) Scenario 2 c) Scenario 3 d) Weight-restricted Scenario 1 e) Weight-restricted Scenario 2 f) Weigh-restricted Scenario 3

5. CONCLUSIONS AND FUTURE WORK

This thesis used a WTW-LCA combined with weight-restricted and unrestricted DEA to quantify 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. 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 findings clearly proved that decarbonization of power generation can lead to favorable results in efficiency performance. This can be seen when taken into account the case of renewable energy-based electricity mix (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 excellent performing category in this scenario. Countries including Romania, Czech Republic, and Estonia should strengthen their EV usage policies for different electricity types. Under all the scenarios, these countries showed below-average performance. The findings in this study thus critically acknowledge the advantage in the use of decarbonized energy supply in the power mix to cut down emissions from all the impact categories. The methods utilized in this thesis can be applied to all countries in the world if the fuel efficiency of EVs is known, the electricity mix, and associated environmental impacts.

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_2 eq., 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 our thesis. Finland is well known for no subsidies and tax incentives when it comes to the use of EVs. However, according to the study conducted in this thesis, Finland is the highest performing country in terms of their use of EVs across Europe under 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. The use of differentiated smart metering systems for EV charging can help in separate taxation for electricity use by EV adopters to take advantage of the government incentives for the use of EVs. To socially optimize the use of EVs on highways, policymakers can implement charges on the amount 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 clean energy sources has become a key overlay in bringing carbon neutral and circular economy opportunities in the transportation industry. For future work, a suggestion to choosing the full ReCipe endpoint impact categories to understand the destructions inflicted on human health, ecosystem health, and resource damage by the use of alternative mobility practices in Europe under the same scenarios using the environmental and social LCA approach. Furthermore, it is suggested to conduct 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 the use of 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 the use of “renewable electricity mix” to avoid the unfair estimation of advantage for EVs. In addition, it is suggested that 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, it is proposed to include more environmental and socioeconomic 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 battery production, automotive part manufacturing, and economy applications of end of life batteries.

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