QATAR UNIVERSITY

COLLEGE OF ENGINEERING

DEA-BASED ELECTRIC VEHICLES EFFICIENCY ASSESSMENT: THE CASE OF THE EUROPEAN UNION COUNTRIES USING MIXED AND SOLAR SOURCES OF ENERGY

BY

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ABSTRACT

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Title: DEA-Based Electric Vehicles Efficiency Assessment: The Case of The European Union Countries Using Mixed and Solar Sources of Energy.

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Adopting electric vehicles (EVs) is represented as a promising solution to have more efficient and sustainable transport systems, European Union (EU) members show a significant interest in adopting EVs, and the governments promote the idea by providing facilities to the buyers. EVs need electricity to operate, which could be generated using mixed sources of energy or solar energy. Generating electricity has environmental and economic impacts. Three environmental indicators (water consumption, GHG emissions, and energy consumption) and one economic indicator (contribution to GDP) for 28 EU countries were used to evaluate the EVs efficiency. An input-oriented single-stage data envelopment analysis (DEA) model was used to obtain the efficiency scores. The k-means clustering algorithm was used to aggregate the 28 countries into high, medium, or low-efficiency groups. Moreover, in this study, total efficiency scores compared using the t-test tool found that using solar energy is more efficient than using mixed-sources of energy.

DEDICATION

This thesis is wholeheartedly dedicated to my father, Tahsin Aljondob, & my mother, Kholoud Qadan, who always picked me up on time, my husband, Mohammed Zarandah, who believes in me, and Respected Qatar University Instructors.

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CHAPTER 1: INTRODUCTION

Several European Union (EU) countries are attempting to shift from Conventional Internal Combustion Vehicles (ICVs) to Battery-Based Electric Mobility (BEVs) in order to reduce emissions and enhance climate-related issues. This chapter highlights the aspects of this technological transformation's environmental impact and the master thesis's contribution. The objectives, research questions, and scopes of this research work are also reported.

1.1 Background

Sustainability worldwide became a requirement to avoid harmful environmental impacts resulting from human activities in different industries. However, the transportation sector is one of the highest causes of environmental impacts in addition to manufacturing and construction Al-Nuaimi, (2020); Kutty et al., (2020a), e.g., in the US, transportation is the second source of Greenhouse Gas emissions (GHG) (Biello, 2007). There is a need to balance the three different pillars for good sustainability performance, where three sustainability pillars, namely: environmental, economic, and social, the environmental and economic pillars are more comfortable to measure than social because both having measurable quantified indicators (Shalabi et al., 2019).

Adopting electric vehicles' (EVs) technology, EVs present a promising solution to avoid the negative impacts of using conventional vehicles, such as greenhouse gas (GHG) emissions, water consumption, and global warming (Egede et al., 2015). Regarding the CO_2 emissions, studies showed that 24% of the emissions came from fuel transportation while EVs decrease this percentage to 10%. Passengers car responsible for 44% of the transportation emissions, and 18% of the emissions came from heavy-duty vehicles, as per the European

Environmental Agency report (EEA, 2020; Tudorie, 2012; Abdella et al., 2017). CO_2 level increased in the atmosphere from 1959 till 2007 from 315 to 380 ppmv which is around 20.6% increment (Black, 2010; Abdella et al., 2019).

1.2 Nonsustainable Transportation Problems

A nonsustainable transportation system has different externalities. Since the start of using vehicles on the road till 2010, around 1 trillion barrels of fuel used to operate vehicles; this large amount of petroleum needed for transportation result in vast impacts on the environment, the world climate change due to GHG emissions to the atmosphere which came out from burning fossil fuel is an example of these impacts.

In the US, the transportation sector is responsible for 32% of CO_2 emissions, where 82% came from gasoline and diesel. Since 1990, CO_2 emissions increasing annually by 1.5%. Local air purity is also affected by unsustainable transportation because of the pollutants emits into the air by vehicle, human health problems related to the respiratory system occur. According to the US's transportation statistics, 68.4% of carbon monoxide emitted into the air by vehicles in 2009. Nevertheless, the unsustainable transportation system causes noise, affecting human well-being, and converts people to anxious moods (Black, 2010). Furthermore, in the EU, around 12% of CO_2 emissions are caused by transportation (Scrosati et al., 2015; Abdella et al., 2019a).

Demirel et al., 2008 state that transportation systems have impacts on 1) water consumption, 2) air quality, 3) GHG emissions, 4) noise and 5) climate change. This study shows that the CO emissions increased in Istanbul by 3.85 times from 1990 to 2000.

1.3 Electric Vehicles

The concept of carbon-neutral mobility has transpired nations around the globe to adopt a transition from a fossil-fueled transit system to a more sustainable carbon-neutral electric mobility (Casals et al., 2016; Abdella et al., 2016). Electromobility has been a priority in member states like the European Union (EU), where the Evs' usage increased to 3.6% in 2019 from 2.5% the preceding year, with nearly 1.8 million cumulative EV registrations to date Cole & Wright, (2003), the EU has set goals to curtail the CO_2 emissions to reach a value of 95 g.CO_2/km capacity by 2020. The standards set for Greenhouse Gas (GHG) emission reduction pathways by the EU have helped bring noticeable growth in EV adoption (Wappelhorst et al., 2020). The adoption of EVs has increased due to both the manufacturers' and users' firm belief in zero-emission mobility alternatives (Amsterdam Round Table Foundation & McKinsey, 2014). Quest for sustainable alternatives for the pressing environmental concerns has also paved the way for EV adoption. According to the studies conducted by Hawkins et al., (2012), Nordelof et al., (2014), and Onat et al., (2018), the critical factors holding a significant impact on the environment are energy consumption and the global warming potential (GWP). Despite studies focusing on the environmental impacts, the social impacts of EV usage have not been quantified through previous research. It is essential to evaluate EVs impactfully to avoid shifting from motorized vehicles to EVs (Egede, 2015).

1.4 Electric Vehicles in the European Union States

From the numbers mentioned above and based on several studies, it is clear why the rapid spreading of sustainability concepts and EVs adoptions worldwide.

European Union states promote EVs usage as a promising solution and an alternative powertrain than conventional vehicles. In 2013, 13% of Norway sales were from BEVs due to the governmental policies that supported the EVs adoption (McKinsey, 2014; Abdella et al., 2020a). Around 1.2 million EVs were on European roads in 2018, but in 2020, EVs reached 8-9 million. Germany exempted taxes from EV owners, where in France, changing a diesel car by EV means the owner will receive back about €11000, in UK EV buyer gets back GBP 4000-7000 depends on the purchasing price if the vehicle emissions less than 75 g/ km. Accordingly, 32000 charging stations were built in the Netherlands (Al-Nuaimi, 2020; McKinsey, 2014). EU states aim to reduce emissions to 95 g CO_2/ km cap at the end of 2020, where the target stated in 2013 to reach 68-78 g CO_2/ km by 2025 (McKinsey, 2014).

1.5 The Efficiency of Electric Vehicles

Electric vehicles are proposed to be a sustainable solution to overcome conventional transportations' negative impacts, especially on the environment (Sikes et al., 2009). Plug-In Hybrid Electric Vehicles (PHEV) has remarkable benefits to the environment, economy, and decreasing petroleum importation. Researchers are discussing the advantages and disadvantages of EV adoption; currently, the conventional transportation system depends on fossil fuel, which is an essential point because it affects the environment a lot, so they need to adopt a new technology depending on the renewable energy source to reduce the environmental impacts (Scrosati et al., 2015; Abdella et al., 2020b). Table 1 shows the advantages and disadvantages of electric vehicles (Herrmann & Rothfuss, 2015; Abdur-Rouf et al, 2018).

Table 1. Advantages and Disadvantages of Electric Vehicles

Area of comparison	Advantage	Example	Disadvantage	Example
Price	Minimize life cycle cost	Less maintenance	Expensive parts	Battery price ≈ \$250-\$600
Environmental impacts	Emission-free system	Zero-CO_2 emissions	Carbon footprint	Currently, not 100% renewable energy, uses mixed-sources energy
Energy storage and charging	Smart solutions of energy	Connecting EV to smart grid	Current infrastructure	Charging stations are not available everywhere

EU set the target to reach 5.75% of fuels in the market to be eco-friendly by 2010 and 10% of renewable energy for the transportation sector by 2020. The usage of EV helps to hit the targets by a factor of 2.5. The EU countries, in 2008, limited NO_2 and PM_{10} concentrations to 40 μg/ m^3/year. In 2010 more than 6% of the population affected by the NO_2 annual concentration mean, which exceeded 40 μg. Generally, the electric vehicle consumes less than half of a conventional vehicle's energy.

EV technology has already shown an improvement in GHG emissions, but also, there is a concern related to the way each county used to generate electric power. In Germany, using nuclear, coal, and renewable energy reduce the impact of generating electricity to operate EVs. However, Poland has a high emission rate due to coal power dependency, increasing the demand for EV evolved to increase the demand for electricity, which may touch the energy future (Helms et al., 2015).

1.6 Research Objectives

This research work aims to:

- Analyze the environmental impacts (water consumption, GHG emissions, and energy consumption) of adopting EVs in 28 EU countries, in the case of using mixed-sources energy and solar energy.

- Assess the efficiency of EV adoption in 28 EU countries, considering the BEVs' life cycle's operational phase. The efficiency across each country was evaluated using three environmental indicators and one economic indicator. Efficiency evaluation was conducted twice for the mixed-sources energy and solar energy.

- Compare the efficiency of adopting EVs using mixed-solar energy and solar energy across the EU countries.

- Rank the 28 EU countries' efficiencies.

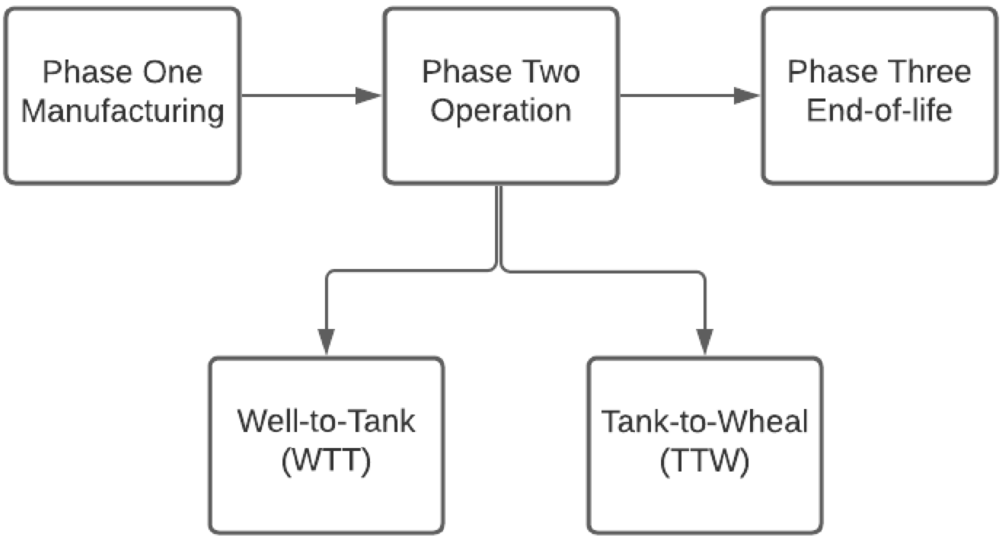

Figure 1. BEVs life cycle phases.

1.7 Research Scope

This study uses Data Envelopment Analysis (DEA) to evaluate the efficiency of adopting BEVs in 28 EU states, considering the life cycle's operational phase. The operational phase is divided into two stages: Well-To-Tank (WTT) and Tank-To-Wheel (TTW), the impacts measured for each stage separately, then aggregated together as Well-To-Wheal (WTW) for calculations. The results obtained from DEA analysis modeled using data visualizing tools to compare the efficiency of adopting mixed-sources energy and solar energy.

This research contribution concentrates on the usage of two different sources of energy and compares the efficiency of each country in both cases, as well as to compare the overall efficiency when adopting EVs using mixed-sources energy and solar energy.

1.8 Research Methodology

This research work accomplished through 5 steps, starting from defining the sustainability indicators, four indicators are chosen, three environmental and one economic, namely, water consumption, energy consumption, GHG emissions, and contribution to GDP. The second step was to collect the data available about each indicator for each of the 28 EU states from the official statistics platforms. After that, correlation analysis was conducted to define the relationship between the indicators, presented by scatter plots and heat maps. Then input-oriented single-stage DEA model was applied twice for each type of energy, the efficiency of each country evaluated at the end of this step. The final step was to model the efficiency results using bar charts, box plot charts, k-means clustering algorithm, and t-test to rank the EU countries.

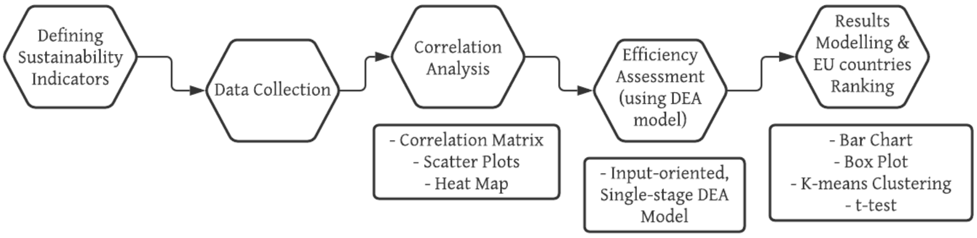

Figure 2. Methodology steps.

1.9 Research Questions

The research questions are one of the essential parts of this research thesis. This research aims to answer the following questions:

Question 1: How efficient is adopting EVs using mixed-sources of energy in 28 EU states?

Question 2: How efficient is adopting EVs using solar energy in different 28 EU states?

Question 3: Which energy source is more efficient in EV adoption?

1.10 Research Limitations

This section will introduce the limitations of the research:

1- Different resources: collecting the data from different resources with different formatting causes a quality reduction in some areas.

2- Data availability: the study started with more than 28 EU countries but due to missing data for some countries they have been excluded from the study. including more countries even from other regions would make the study more comprehensive.

3- SI selection: selecting the SI also was limited to the data available from each country on the official websites, having more SI would make the study more accurate and make the evaluation more realistic.

CHAPTER 2: LITERATURE REVIEW

2.1 The Definition of Sustainable Transportation

This section is dedicated to understanding what does it mean sustainability in transportation.

In 1987 a report from the United Nations Commissions On Environment And Development stated the definition of sustainability Brundtland et al., (1987), from that definition, sustainability in transportation has been defined as "satisfies the current transport and mobility needs without compromising the ability of future generations to meet these needs." This definition slightly changed from one rejoin to another, e.g., in Canada, transport Canada defined sustainable transportation as affordable service, has no impact on the environment in a fair manner. Moreover, in Europe, sustainable transportation is defined as sustainable mobility (Black, 2010; Alsarayreh et al., 2020).

2.2 Electric Vehicle Sustainability Assessment

The efficiency Assessment (EEA) considers measuring the environmental impacts and the economic benefits using selected indicators covering both the sustainability dimensions. The EEA under high dimensional settings of indicators is a challenge to the complexity of the EEA. Several methods have been proposed and utilized over the last years to overcome such a challenge. Linear programming simplifies the sustainability assessment complexity of sustainability in multi indicators with different measuring units. Two widely used techniques to reduce complexity are Data Envelopment Analysis (DEA) and Principal Component Analysis (PCA) (Al-Nuaimi, 2020; Al-Sheeb et al., 2019).

Several studies conducted the efficiency assessment of e-mobility in different regions, taking into account the variety of energy sources and EV types. These studies' common objective is to prove the efficiency of EVs adoptions instead of conventional vehicles regarding environmental, economic, and less focusing on social impacts (Elhmoud and Kutty, 2021; Kucukvar et al., 2019).

The primary approach used for assessing EVs' efficiency is the Life Cycle Assessment (LCA) (Onat et al., 2018; Kim et al., 2019; Onat et al., 2021). The reason behind using LCA is its ability to analyze the environmental impacts through all phases of the life cycle, starting from the extraction of raw materials phase down to the end-of-life (Heijungs et al., 2010; Kucukvar et al., 2014a; Onat et al., 2014; Tatari et al., 2015; Abdella et al., 2021).

A study conducted by Baral et al., (2021), Kucukvar et al., (2014) using Social LCC found that using EVs results in a reduction in cost and carbon footprint and less energy consumption than diesel vehicles. Two different comparisons for full life cycle assessment are made in the literature targeted the US region to compare the efficiency of different EVs, naming of them HEV, BEV, Plug-in Hybrid Electric Vehicles (PHEV), and Sport Utility Vehicles (SUV). Considering the Global Warming Potential (GWP) Karaaslan et al., (2018), BEVs have the lowest GWP, 233 g CO_2-eq/km. The highest is Gasoline ICV with 589 g CO_2-eq/km, where Duvall (2002) said that PHEVs with GWP equals 159 g CO_2-eq/km are the lowest Gasoline ICV are the highest 388 g CO_2-eq/km.

Onat et al., (2020) concluded that BEVs have the minimum GWP 69 g CO_2-eq/km and Gasoline ICVs are the maximum 355 g CO_2-eq/km while considering the Wheel to Wheel (WTW) phase, where Nordelof et al. (2014); Kutty et al., (2020b) found that the lowest GWP 265 gCO_2-eq/km belongs to HEVs and the highest GWP 350 gCO_2-eq/km belongs to Gasoline ICVs for the same phase WTW. As EVs reduce the environmental impacts of traditional transportation systems, especially the CO_2

emissions, this is reflected as a health benefit to the society and reduced the costs of health aids needed due to pollution, as studied in the US (Malmgren, 2016).

Onat et al., (2020); Kutty et al., (2020c) after applying the LCC approach, it shows that BEVs' total ownership cost is lower than ICVs. From a social perspective, ICVs have the highest taxes generated and employment, while using solar energy for EVs, these social benefits decrease. On the other hand, economically replacing a Honda Civic with Nissan Leaf would save fuel usage over ten years of a vehicle lifetime about $4130, also comparing traditional vehicles with EVs from operation and maintenance cost point for a lifetime (120,000 miles), EV saves approximately $1488 (Malmgren, 2016).

For EU countries AlNuaimi, (2020) found, the highest efficient countries are Austria and Belgium, where the Czech Republic and Bulgaria have the lowest efficiency performance; note that only the operational phase was taken into account.

The efficiency assessment of electric vehicles could be done from different perspectives. Some studies are cradle-to-gate Philippot et al., (2019), where others are concerned about only one phase of the vehicle life cycle Faria, et al., (2013) studied the GHG emissions result through the operational phase only of the PHEV and conventional vehicles. EVs lifecycle is divided into three phases: manufacturing, operation, and end-of-life. Studies assess different product sustainability using Life Cycle Assessment (LCA) in 1991 by assessing its environmental impacts from the manufacturing phase to the recycling/ end-of-life phase. LCA helps quantify a product's environmental impacts through its life cycle (Onat et al., 2014). LCA approach can customize the component through the product life cycle, which helped LCA become widely used in industrial and academic sectors (Curran, 1996; Egilmez and Park, 2014). The literature then found that LCA was used to assess alternative systems Onat, (2015a); Onat, (2015b); Onat et al., (2016b) also by measuring carbon emissions Samaras and Meisterling, (2008) used LCA to assess the impacts of plug-in electric vehicles. Although a comparison was conducted by Onat et al., (2014) between different US vehicles to compare energy usage and GHG emissions using the LCA approach, 19 sustainability indicators, and three charging scenarios where the vehicles included in the study are PHEVs, HEVs, BEVs, and conventional vehicles. Also, LCA was employed to assess gasoline vehicles' impacts versus EVs (Faria et al., 2012). Besides, assessing the environmental impacts of conventional vehicles and alternative powertrain vehicles in different regions was conducted in several studies (Yagcitekin et al., (2015) in Turkey; Nanaki and Koroneos, (2013) in Greece).

Gloria et al., (2007) developed a new approach to overcome this limitation, which is Life Cycle Sustainability Assessment (LCSA); the new LCSA involves the previously known LCA approach, Social Life Cycle Assessment (SLCA), and Life Cycle Costing (LCC). A comprehensive LCSA model was utilized to evaluate the impact of 19 indicators relevant to social, economic, and environmental dimensions for alternative vehicle technologies in the US (Onat et al., 2014). However, Life Cycle Cost (LCC) is an economic assessment tool used to emphasize the total related cost for purchasing, operating, and recycling the product. For HEV, LCC used to assess four cost elements that affect adopting HEV; these factors are initial costs, maintenance costs, annual fuel costs, and insurance costs. (Onat et al., 2020). Another sustainability assessment tool used by researchers, Input-Output Life Cycle Assessment (IO-LCA), is widely used when the system is large-scaled such as transportation; IO-LCA gives better economic analysis (Onat et al., 2014). This hybrid IO-LCA was used by Karaaslan et al., (2018) to evaluate the full life cycle of

PHEV, Gasoline internal combustion vehicles (ICV), diesel ICV FCEV, and BEV.

2.3 DEA Approach of Efficiency Analysis

The DEA is a method used to determine the ability to convert the inputs into outputs and calculating the efficiency frontier (Neves et al., 2020). In addition to that, DEA has an advantage where it does not require a defined mathematical relationship between inputs and outputs (Tudorie, 2012).

The DEA used by Neves et al., (2020) in two stages format firstly evaluates the BEV policies in Europe and the adoption. EVs consume different energy types such as gas, diesel, fully electricity, or hybrid gas/ electricity. From this point, DEA utilized by Partovi and Kim (2013) to compare the efficiency of these vehicle categories to fuel vehicles. Numerous studies applied PCA to assess the efficiency of e-mobility because it allows the composite of the indicators, which makes more straightforward computation. Then PCA was used to reduce the dimensions between feature vectors of electric vehicles, which helped keep the original information (Yu et al., 2020).

In addition to the mentioned tools utilized for efficiency assessment, DEA is a wild used tool to assess efficiency in different fields. It is a powerful decision-making method used to evaluate the transportation systems' performance and the sustainability improvement level achieved by EV adoption (Onat et al., 2017). DEA is a suitable approach to assess a systems' environmental impacts. Note that the DEA results have high sensitivity to the correlation between SIs (Onat et al., 2019).

Before conducting the DEA model, identifying the models' inputs and outputs considered the first step, e.g., for BEV sustainability assessment water consumption, and energy consumption are the inputs, and the GHG emissions and costs are the outputs. After defining the indicators, researchers decided to use an input-oriented DEA model, minimizing resource consumption (Onat et al., 2017).

Onat et al., (2019) applied PCA to evaluate the eco-efficiency of electric vehicles in the US while using the results obtained from applying DEA as a benchmark (Onat et al., 2017). Onat et al., (2017) used the LCA combined with the DEA to evaluate BEV efficiency through the operational phase. Utilizing DEA helped to weigh and unify the environmental indicators without using any weighting approach separately. From a different perspective Neves et al., (2020), perform a two-stage DEA model, output-oriented to provide a clear perception of the BEV market. 20 EU countries involved in the study, the first stage calculated the efficiency of BEV adoption and policies supporting it. The second DEA stage was conducted to calculate EV's problems by using the fractional regression model. According to the obtained results, few countries are efficient in BEV adoption but using renewable energy makes inefficient countries closer to the frontier.

Iftikhar et al., (2018) conducted DEA free line model to analyze the CO_2 emissions and energy consumption in 19 major economics these are granted up to 65% of the worldwide GDP, found that 89% of emitted CO_2 and 85% of consumed energy are related to the inefficient distribution systems. As well, due to the rapid growth in the German cities, air quality and environmental problems increased, then to keep the standards of living in the cities at an acceptable level, air quality in urban areas analyzed using Stochastic Fortier Analysis (SFA) and DEA in 24 German cities after that fractional regression applied to study the factors affecting the efficiency scores (Moutinho et al., 2020). DEA has been expanded to involve a network of DMUs, and Network DEA (NDEA) developed to measure efficiency (Cook & Zhu, 2014). NDEA integrated to Slack-Based-Model (SBM-NDEA) be more general and efficient in assessing the efficiency Boloori & Pourmahmoud, (2016) utilized SBM-NDEA to analyze bank branches efficiency. Still, NDEA is a rarely used technique (Iftikhar et al., 2018).

Nevertheless, in China, the transportation system contributes to environmental problems, then Tian et al., (2020) performed an output-oriented Slacks-Based measure DEA (SBM-DEA) to assess China's transportation efficiency. In the proposed model, thirteen input and seventeen output indicators were used related to four dimensions: environmental, social, economic, and system effectiveness.

CHAPTER 3: ASSESSMENT METHODOLOGY

This chapter describes step by step with details the method conducted to implement electric vehicle efficiency assessment in the 28 selected EU countries for the mixed-sources of energy and solar energy used to generate electricity for BEVs.

Step 1: Recognizing Sustainability Indicators

The sustainability indicators (SIs) selection is a random process, where the selected SIs must match the research's contribution, showing the impact that the researcher is trying to highlight. The SIs need to be quantified, valid, and accurate (Mascarenhas et al., 2015). This research aims to assess BEVs' efficiency in the operational phase while using mixed energy and solar energy source to generate electricity. Three environmental indicators and one economic indicator were selected (see Table 2). These are 1) water consumption, 2) GHG emissions, 3) energy consumption. The contribution to the GDP is selected to represent the economic value added.

Table 2. Sustainability Indicators and Measuring Units

Sustainability Pillar	Indicator	Category	Measuring Unit
Environmental	Water Consumption	Environmental impact indicators	L/kWh
	GHG Emissions		g CO_2-eq /kWh
	Energy Consumption		kWh/kWh
Economic	Contribution to GDP	Value-added	US Dollar

Step 2: Data Collection and Description

This study used Eurostat, World Energy Statistics, and Electricity Information databases to generate the electricity data for the 28 EU countries.

"Nissan" is the brand used to assess EV's impact, taking into account the energy consumption kilo-watt hour for the vehicles to be (30 kWh per 100 miles). Onat et al., (2018), studied the water consumption per source. These data were utilized in this research. Tables 3 and 4 show the data collected and calculated statistics related to EV impacts using the mixed-sources of energy.

Table 3. BEV Impacts on Water Consumption, GHG Emissions, and Energy Consumption Using Mixed-Sources of Energy

Country Name	Water Consumption (L/kWh)	GHG Emissions (g CO_2-eq /kWh)	Energy Consumption (KWh)
Austria	4.36929	27.71949	0.36368
Belgium	0.0641865	37.53556	0.51231100
Bulgaria	1.129286	81.82953	0.54275500
Croatia	0.43818	109.3283	0.80456800
Cyprus	0.912432	96.75639	0.63678600
Czech Republic	0.477689	65.57607	0.61871300
Denmark	0.684131	138.1265	0.74500300
Estonia	2.045583	40.62766	0.55610800
Finland	1.251493	16.90432	0.39942200
France	0.819331	89.62607	0.61367300
Germany	0.910118	93.36113	0.57678000
Greece	0.644032	55.75293	0.56073700
Hungary	3.520328	54.30764	0.42011200
Ireland	0.604039	90.48596	0.59500800
Italy	1.25495	73.26752	0.57232900

Country Name	Water Consumption (L/kWh)	GHG Emissions (g CO_2-eq /kWh)	Energy Consumption (KWh)
Latvia	4.296438	43.84821	0.49963200
Lithuania	1.978646	34.35064	0.46174000
Luxembourg	4.643965	17.57475	0.35366100
Malta	0.311266	54.95698	0.49075400
Netherlands	0.494004	107.1207	0.67730500
Portugal	0.774351	141.2529	0.71760400
Poland	1.241278	63.00720	0.49080400
Romania	2.032198	62.65153	0.46177100
Slovakia	1.811014	35.67368	0.47470700
Slovenia	2.312061	60.09141	0.47932900
Spain	0.951458	53.73154	0.47078700
Sweden	3.191355	8.60436	0.35101400
UK	0.646797	64.38545	0.60649600

Table 4. BEV Impacts Statistics Using Mixed-Sources of Energy

Variable	N	Min	Max	Mean	SD (σ)
Water Consumption	28	0.3113	4.464	1.5853	1.2883
GHG Emissions	28	8.6044	141.253	64.9448	34.1626
Energy Consumption	28	0.3510	0.8046	0.5376	0.1157

Tables 5 and 6 show the data collected and calculated statistics related to EV impacts using solar energy.

Table 5. BEV Impacts on Water Consumption, GHG Emissions, and Energy Consumption Using Solar Energy

Country Name	Water Consumption (L/kWh)	GHG Emissions (g CO_2-eq /kWh)	Energy Consumption (KWh)
Austria	0.09	0.13	0.19
Belgium	0.1	0.15	0.19
Bulgaria	0.13	0.2	0.19
Croatia	0.17	0.26	0.19
Cyprus	0.1	0.16	0.19
Czech Republic	0.1	0.15	0.19
Denmark	0.1	0.15	0.19
Estonia	0.09	0.14	0.19
Finland	0.13	0.19	0.19
France	0.1	0.15	0.19
Germany	0.15	0.22	0.19
Greece	0.12	0.19	0.19
Hungary	0.13	0.2	0.19
Ireland	0.1	0.15	0.19
Italy	0.15	0.22	0.19
Latvia	0.1	0.16	0.19
Lithuania	0.1	0.16	0.19

Country Name	Water Consumption (L/kWh)	GHG Emissions (g CO_2-eq /kWh)	Energy Consumption (KWh)
Luxembourg	0.1	0.15	0.19
Malta	0.14	0.21	0.19
Netherlands	0.1	0.15	0.19
Portugal	0.1	0.15	0.19
Poland	0.12	0.18	0.19
Romania	0.14	0.2	0.19
Slovakia	0.11	0.17	0.19
Slovenia	0.09	0.13	0.19
Spain	0.11	0.17	0.19
Sweden	0.09	0.13	0.19
UK	0.1	0.15	0.19

Table 6. BEV Impacts Statistics Using Solar Energy

Variable	N	Min	Max	Mean	SD (σ)
Water Consumption	28	0.09	0.17	0.1129	0.02158
GHG Emissions	28	0.13	0.26	0.1704	0.03214
Energy Consumption	28	0.19	0.19	0.19	8.47947E-17

Step 3: Investigating the Correlation within Sustainability Indicators

In this study, the pair correlation function $p_{(r_{ij})}$ was applied to investigate the relationship between all possible pairs of the selected ith and jth SIs. The pair correlation function measures how far the pair is from unity. That is why the maximum correlation factor is 1; however, 0 indicates no correlation. In literature, this method is widely used, where ${r_{ij}}^2$ could help measure the model efficiency and to which level the model is representative in terms of the used dataset (Van Leeuwen et al., 1959; Abdella & Shaaban, 2020).

Figure 3 shows the correlation relationship between the environmental indicators while using the mixed-sources of energy.

	Water Consumption	GHG Emissions	Energy Consumption
Water Consumption	1	-0.589116832	-0.692959325
GHG Emissions	-0.589116832	1	0.889893412
Energy Consumption	-0.692959325	0.889893412	1

Figure 3. Correlation matrix for EV impact on GHG emissions, water, and energy consumption: The case of using mixed-sources energy.

Its clear from the correlation matrix that the water consumption impact and the GHG emissions impact indicators are negatively correlated by approximately -0.589, which means when the impact of water consumption increases, the GHG emissions impact decreases, and vice versa are dependent on each other. Also, the matrix shows a negative correlation by approximately -0.693 between the water consumption impact and the energy consumption impact; these two indicators are dependant on each other if the water consumption impact increases, then the energy consumption impact will decrease if the water consumption decrease then the energy consumption will increase. The difference between the correlation impacts between water consumption with GHG emission and water consumption with energy consumption is 0.104, which describes that GHG emission has a small impact on water consumption, which can be ignored compared to the impact of energy and energy consumption.

Moreover, a positive correlation between GHG emissions impact and energy consumption impact by approximately 0.890 means both depend on each other. When the GHG emissions impact increases, then the energy consumption impact increases as well, and the opposite is also correct.

Figure 4 shows the correlation relationship between each indicator and others, clearly showing the positive impact of GHG emissions impact and energy consumption impact.

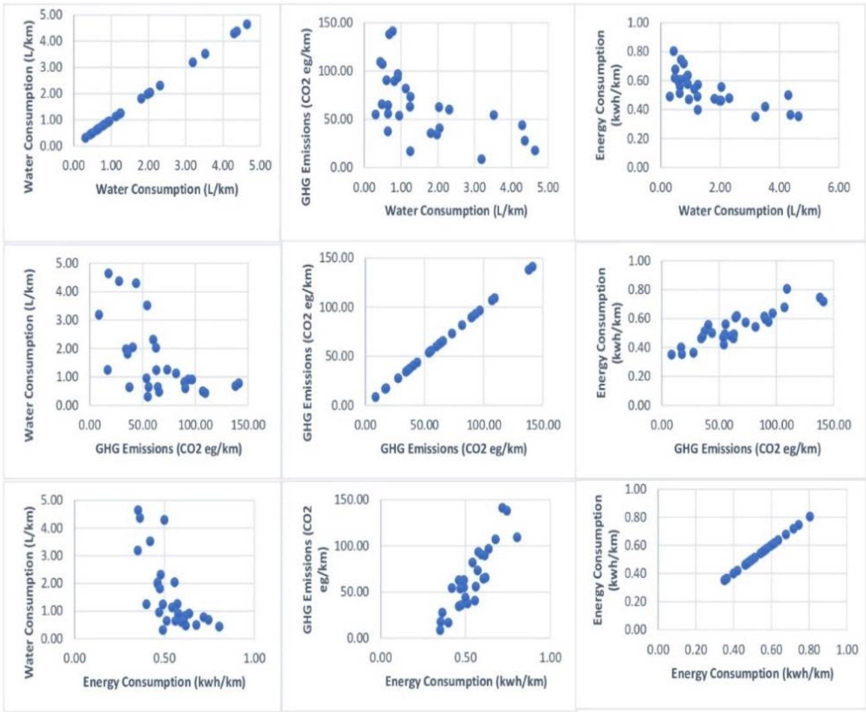

Figure 4. Correlation scatter plots of EV impact on GHG emissions, water consumption, and energy consumption: The case of using mixed-sources energy.

The second scenario is using solar energy to generate electricity. Figure 5 shows the correlation relationship between the environmental indicators while using solar energy.

	Water Consumption	GHG Emissions	Energy Consumption
Water Consumption	1	0.986356397	1.95E-16
GHG Emissions	0.986356397	1	4.82E-16
Energy Consumption	1.95E-16	4.82E-16	1

Figure 5. Correlation matrix for EV impact on GHG emissions, water, and energy consumption: The case of using solar energy.

The correlation between water consumption impact and the GHG emissions impact is a high positive correlation around 0.99. That means both impacts are changing in the same direction. If water consumption impact increases, then the GHG emissions increase and vice versa. The line between the water consumption impact and the GHG emissions impact is almost an increasing straight line, as shown in Figure 6. However, the correlation between the water consumption impact and energy consumption impact and the correlation between GHG emissions impact and the energy consumption are represented as positive values $1.95*10^{-16}$ and $4.82*10^{-16}$. These two values are almost equal to zero, which means no correlation between the mentioned indicators. The relationships are presented in Figure 6 clearly between the matrix elements.

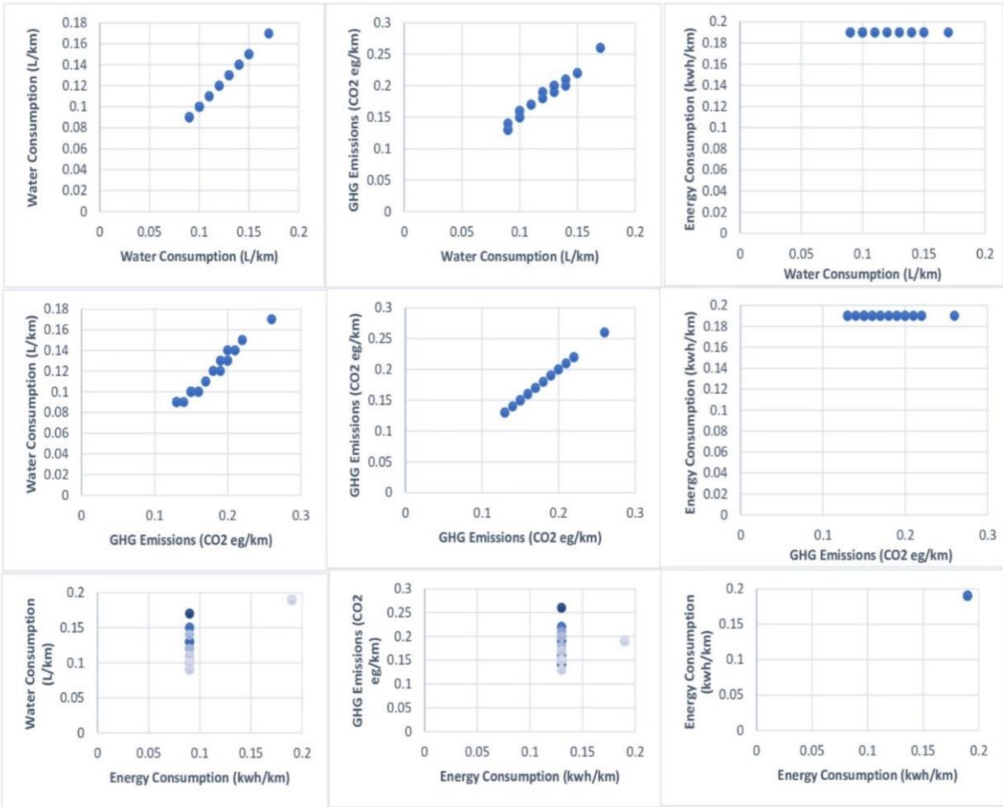

Figure 6. Correlation scatter plots of EV impact on GHG emissions, water consumption, and energy consumption: The case of using solar energy.

The heat map is used to identify the correlation relationship between the environmental indicators. Figure 7 shows the environmental indicators data for EVs impacts using the mixed-sources of energy, where Figure 8 shows data related to solar energy use.

	Water Consumption (L/kWh)	GHG Emissions (g CO_2-eq /kWh)	Energy Consumption (KWh)
Austria	4.36929	27.71949	0.36368
Belgium	0.0641865	37.53556	0.512311
Bulgaria	1.129286	81.82953	0.542755
Croatia	0.43818	109.3283	0.804568
Cyprus	0.912432	96.75639	0.636786
Czech Republic	0.477689	65.57607	0.618713
Denmark	0.684131	138.1265	0.745003
Estonia	2.045583	40.62766	0.556108
Finland	1.251493	16.90432	0.399422
France	0.819331	89.62607	0.613673
Germany	0.910118	93.36113	0.57678
Greece	0.644032	55.75293	0.560737
Hungary	3.520328	54.30764	0.420112
Ireland	0.604039	90.48596	0.595008
Italy	1.25495	73.26752	0.572329
Latvia	4.296438	43.84821	0.499632
Lithuania	1.978646	34.35064	0.46174
Luxembourg	4.643965	17.57475	0.353661
Malta	0.311266	54.95698	0.490754
Netherlands	0.494004	107.1207	0.677305
Portugal	0.774351	141.2529	0.717604
Poland	1.241278	63.0072	0.490804
Romania	2.032198	62.65153	0.461771
Slovakia	1.811014	35.67368	0.474707
Slovenia	2.312061	60.09141	0.479329
Spain	0.951458	53.73154	0.470787
Sweden	3.191355	8.60436	0.351014
UK	0.646797	64.38545	0.606496

0.0641 141.3

Figure 7: Heat map of sustainability indicators data for EV impacts using mixed-sources energy.

	Water Consumption (L/kWh)	GHG Emissions (g CO_2-eq /kWh)	Energy Consumption (KWh)
Austria	0.09	0.13	0.19
Belgium	0.1	0.15	0.19
Bulgaria	0.13	0.2	0.19
Croatia	0.17	0.26	0.19
Cyprus	0.1	0.16	0.19
Czech Republic	0.1	0.15	0.19
Denmark	0.1	0.15	0.19
Estonia	0.09	0.14	0.19
Finland	0.13	0.19	0.19
France	0.1	0.15	0.19
Germany	0.15	0.22	0.19
Greece	0.12	0.19	0.19
Hungary	0.13	0.2	0.19
Ireland	0.1	0.15	0.19
Italy	0.15	0.22	0.19
Latvia	0.1	0.16	0.19
Lithuania	0.1	0.16	0.19
Luxembourg	0.1	0.15	0.19
Malta	0.14	0.21	0.19
Netherlands	0.1	0.15	0.19
Portugal	0.1	0.15	0.19
Poland	0.12	0.18	0.19
Romania	0.14	0.2	0.19
Slovakia	0.11	0.17	0.19
Slovenia	0.09	0.13	0.19
Spain	0.11	0.17	0.19
Sweden	0.09	0.13	0.19
UK	0.1	0.15	0.19

0.09 0.26

Figure 8: Heat map of sustainability Indicators data for EV impacts using solar energy.

Step 4: EV Efficiency Assessment Using Input-oriented Single-stage DEA Model

An input-oriented single-stage DEA model was applied twice to assess the EV efficiency in each of the selected 28 EU countries while using mixed-source energy and solar energy. DEA calculated the DMU's efficiency concerning other DMUs, the ratio of output over input was used to present each country's efficiency. The three environmental indicators are used as input DMUs, where the economic indicator is the output DMU. The input-oriented DEA objective is to minimize the inputs (see Equation 1) because the less water, energy consumption, and GHG emissions, the better the transportation system. The most efficient countries have E=1, where the less efficient countries have E < 1. To reach the target of minimizing the objective function z the model needs to satisfy a group of constraints. Output over input ratio must be less than or equal to 1 as expressed in Equation 2, which means the sum of the three input DMUs (denominator) should be less than or equal to the output (numerator). Equations 3 and 4 are concerned with the weight coefficients. Each of the indicators is given a weight according to its importance. However, decision variables are nonnegative, so that weights could be zero or more (Abdella et al., 2021a). Model constraints apply to all DMUs from i to N.

$$min\ z = \frac{uy_j}{\sum_{i=1}^{N} v_i\ x_{ij}} \tag{1}$$

Subject to

$$uy_k / \sum_{i=1}^{N} v_i\ \ x_{ik} \leq 1; \quad k = 1, \ldots, n \tag{2}$$

$$u \geq 0 \tag{3}$$

$$v_i \geq\ 0; \quad i = 1, \ldots, N \tag{4}$$

where u = output multiplier, v_i= input multiplier, j the evaluated DMU, N = number of inputs, k = numbers of DMUs, $y_k =$ the amount of output produced by the DMU k, $x_{ik} =$ the amount of input i used by the DMU k, z is the objective function that aims to minimize the inputs. The DMU with the minimum inputs is considered as the efficient DMU.

After running the data related to using the mixed-sources of energy, DEA efficiency results for each of the 28 EU countries were shown in Table 7.

Table 7. DEA Efficiency Scores for EU Countries Using Mixed-Sources of Energy

No.	Country Name	Efficiency	No.	Country Name	Efficiency
1	Austria	0.977	15	Italy	0.772
2	Belgium	1.000	16	Latvia	0.586
3	Bulgaria	0.325	17	Lithuania	0.416
4	Croatia	0.804	18	Luxembourg	0.836
5	Cyprus	0.411	19	Malta	0.660
6	Czech Republic	1.000	20	Netherlands	0.508
7	Denmark	0.329	21	Portugal	0.388
8	Estonia	0.526	22	Poland	0.830
9	Finland	1.000	23	Romania	0.520
10	France	0.897	24	Slovakia	0.562
11	Germany	0.557	25	Slovenia	0.596
12	Greece	0.381	26	Spain	0.997
13	Hungary	0.572	27	Sweden	1.000
14	Ireland	0.701	28	UK	0.569

The second DEA run was to evaluate the efficiency while using solar energy; Table 8 shows each country's efficiency.

Table 8. DEA Efficiency Scores for EU Countries Using Solar Energy

No.	Country Name	Efficiency	No.	Country Name	Efficiency
1	Austria	1.000	15	Italy	0.580
2	Belgium	0.868	16	Latvia	0.818
3	Bulgaria	0.650	17	Lithuania	0.827
4	Croatia	0.497	18	Luxembourg	0.835
5	Cyprus	0.824	19	Malta	0.613
6	Czech Republic	0.855	20	Netherlands	0.866
7	Denmark	0.838	21	Portugal	0.830
8	Estonia	0.915	22	Poland	0.721
9	Finland	0.672	23	Romania	0.630
10	France	0.834	24	Slovakia	0.754
11	Germany	0.579	25	Slovenia	0.980
12	Greece	0.692	26	Spain	0.766
13	Hungary	0.652	27	Sweden	0.957
14	Ireland	0.884	28	UK	0.886

The reason behind selecting DEA is the comparison purpose, as DEA based on comparison and the DMUs are evaluated against each other, where the objective of this research is to find out which type of energy is more efficient in EVs adoption, and how efficient is the performance in each country. Also, DEA could generate the weight of inputs and outputs through the optimization methods based on the objective. Lastly, DEA has the advantage to be integrated into different methods to achieve the desired results according to the evaluation field.

Step 5: Modelling Efficiency Results and Ranking EU

To simplify reading the results and Figure out the most efficient country in utilizing the two different energy types. The obtained results were modeled and clustered using the bar chart. Figure 9 shows the first DEA run related to using mixed-sources energy, while Figure 10 shows the DEA results when using solar energy.

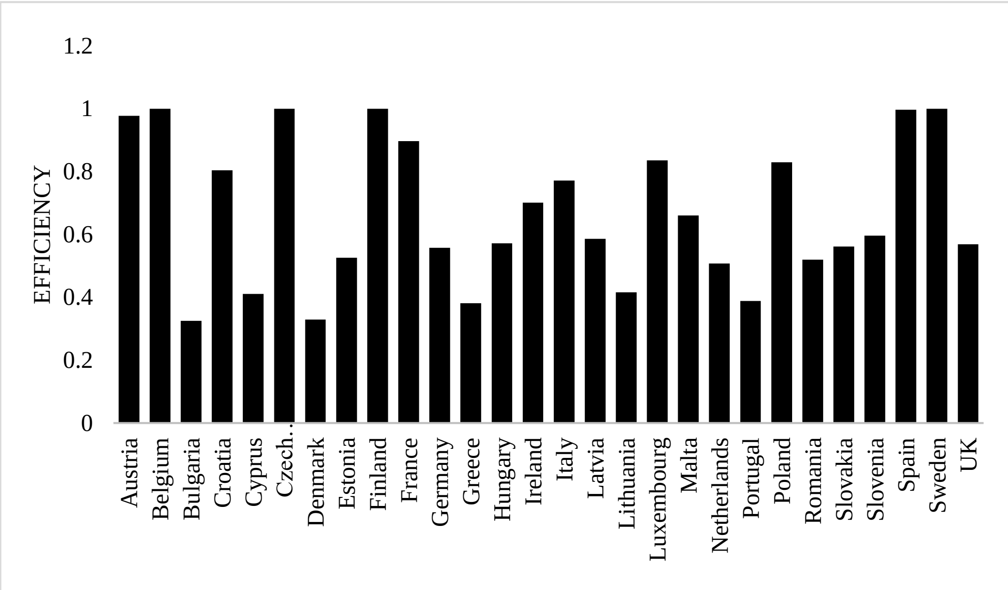

Figure 9. Efficiency results for 28 EU countries using mixed-sources of energy.

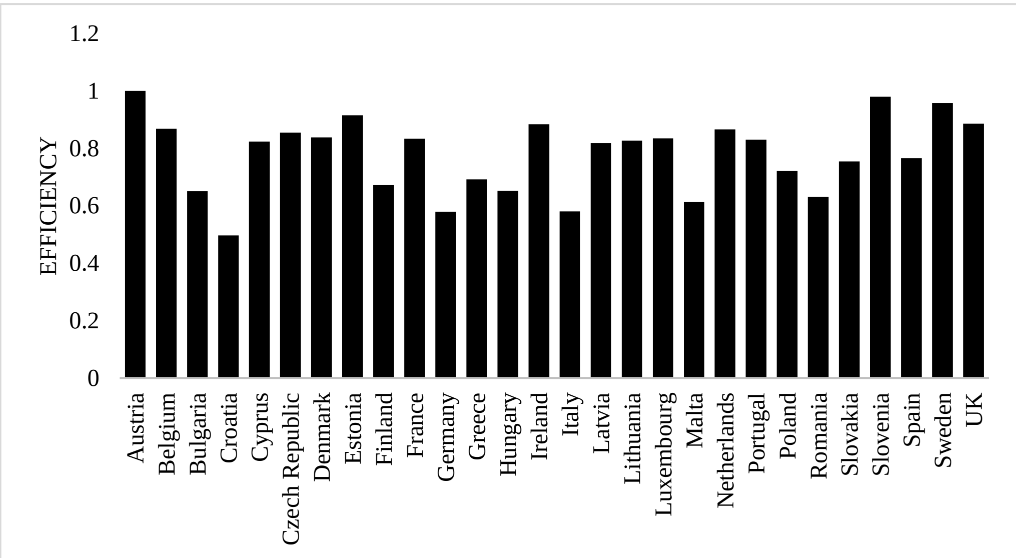

Figure 10. Efficiency results for 28 EU countries using solar energy.

The 28 EU countries were ranked from the most efficient to the least in each case; see Table 9.

Starting with the first case when using mixed-sources energy, the most efficient countries are Belgium, Czech Republic, Finland, and Sweden, with an efficiency score equal to 1. On the other hand, the least efficient countries are Bulgaria, Denmark, Greece, and Portugal, with efficiency scores 0.325, 0.329, 0.381. 0.388 respectively.

Moreover, in the case of using solar energy, the most efficient country is Austria, with efficiency equal to 1, Slovenia is the second country with a score equal to 0.98, followed by Sweden 0.957 and Estonia 0.951. for the least efficient countries, Croatia scored the lowest efficiency 0.497, then Germany 0.579, Italy 0.580, and Romania 0.630.

Table 9. The Most and Least Efficient EU Countries

Type of Energy	Most Efficient EU Countries	Least Efficient EU Countries
Mixed-Sources Energy	Belgium, Czech Republic, Finland, Sweden.	Bulgaria, Denmark, Greece, Portugal.
Solar Energy	Austria, Slovenia, Sweden, Estonia.	Croatia, Germany, Italy, Romania.

CHAPTER 4: EVs EFFICIENCY ANALYSIS AND COMPARISON

This chapter reports the EVs' impact on the three environmental indicators and the economic indicator while using mixed-sources energy and solar energy.

4.1 EVs Impact on Water Consumption

EVs significantly impact water consumption during generating electricity while using mixed-sources of energy; Figure 11 shows the water consumption impacts in descending order. Luxembourg has the highest impact on water consumption, which is around 4.64 (L/km), equivalent to 10.5 % of the total water consumption. Where Malta scored 0.311 (L/km), and it is the lowest impact on water consumption.

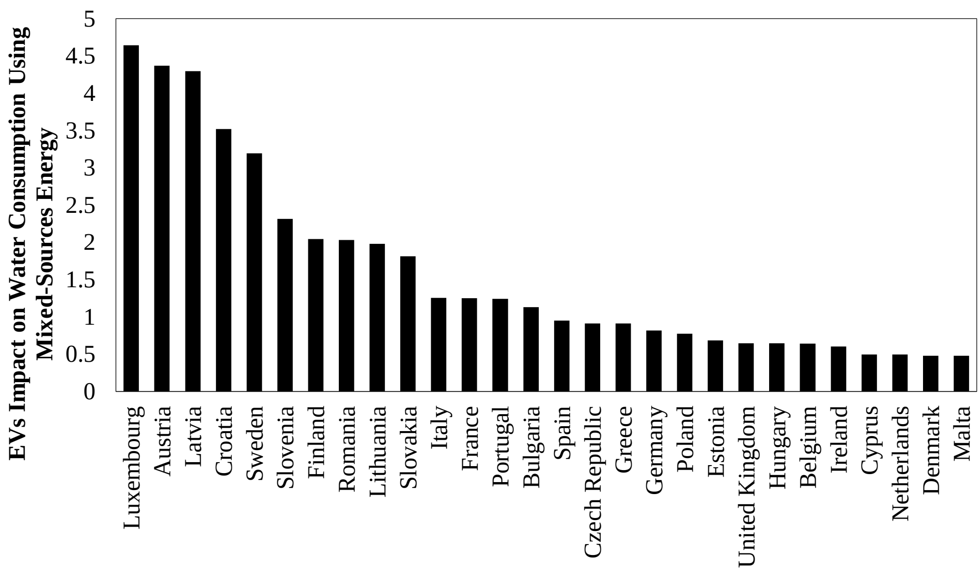

Figure 11. EVs impact on water consumption using mixed-sources of energy.

On the other hand, the EVs impact water consumption while using solar energy in the 28 EU countries shown in Figure 12. The maximum impact is 0.17 (L/km) scored by Cyprus, representing 5.4% of the total water consumption. Moreover, the minimum impact is 0.09 (L/km) scored by Austria.

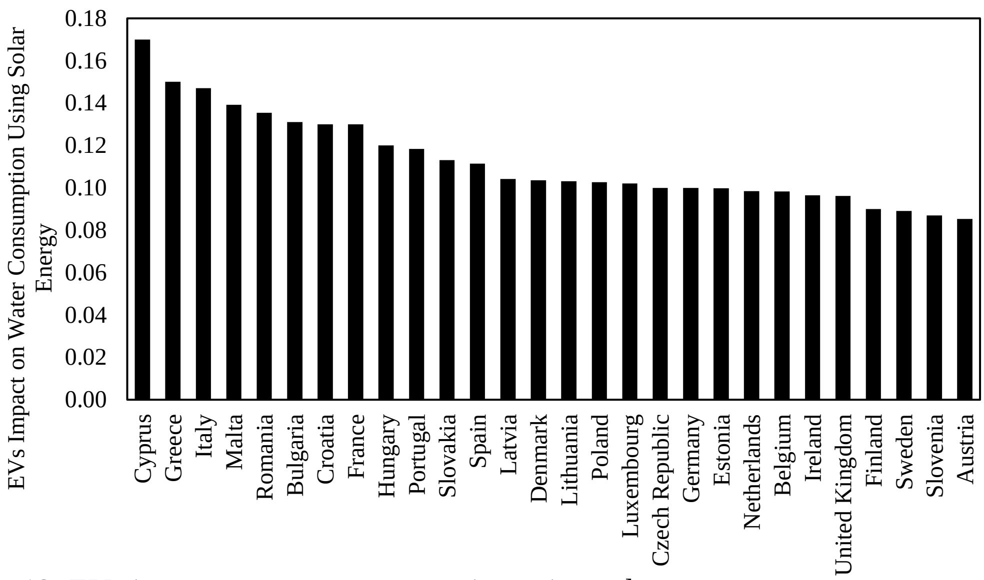

Figure 12. EVs impact on water consumption using solar energy.

The maximum impact from using solar energy is less than the maximum impact from using mixed-sources energy. Then using solar energy to generate electricity is more efficient from the water consumption perspective.

4.2 EVs Impact on GHG Emissions

Figure 13 shows the EVs' impact on GHG emissions (CO_2 equivalent g/km) when using mixed-sources of energy, where Figure 14 shows the impact of solar energy usage. The highest impact recorded from mixed-source energy usage is for Poland 141.25 (CO_2 equivalent g/km), followed by Estonia 138.1 (CO_2 equivalent g/km), Poland and Estonia are responsible for 15.5 % of the total emitted greenhouse gases. The lowest is 8.6 (CO_2 equivalent g/km) emitted by Sweden. The solar energy impact shows the highest emissions in Cyprus 0.26 (CO_2 equivalent g/km), where Sweden emitted the lowest 0.13 (CO_2 equivalent g/km). A noticeable difference was found between the amount of GHG emissions from mixed-sources energy and solar energy. Using solar energy reduces GHG emissions and leads to a more efficient transport system with fewer environmental impacts.

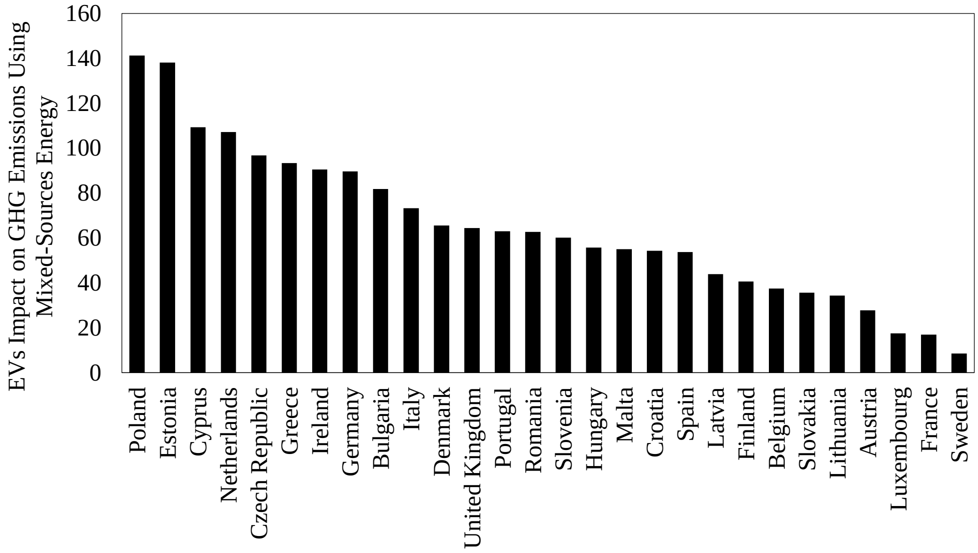

Figure 13. EVs impact on GHG emissions using mixed-sources of energy.

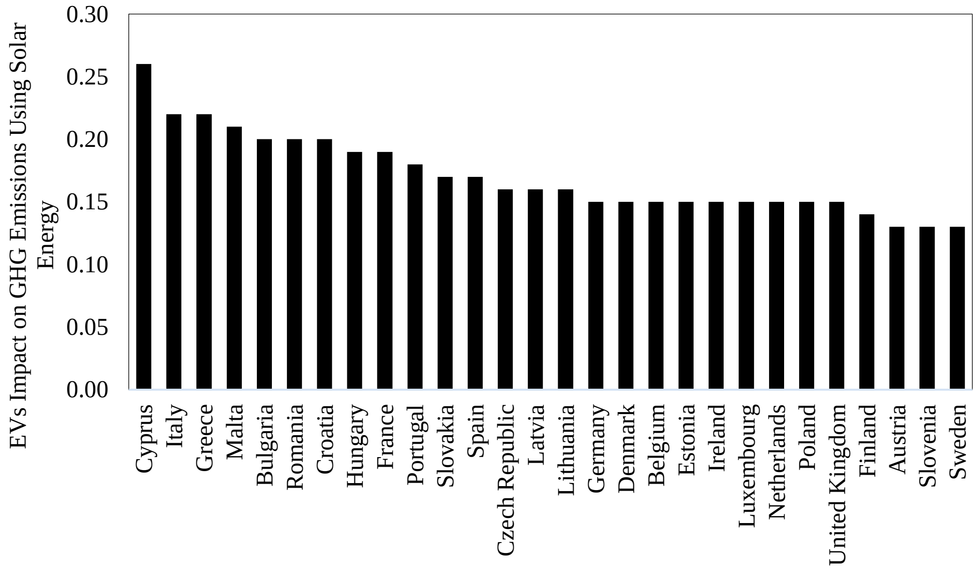

Figure 14. EVs impact on GHG emissions using solar energy.

4.3 EVs Impact on Energy Consumption

Generating electricity using a mixed-source of energy means more energy to consume than solar energy for the same purpose. Cyprus has the highest EVs score impacting energy consumption, approximately 0.80 (kwh/km), around 5.3 % of the total energy consumption. Sweden has the lowest impact, approximately 0.35 (kwh/km) (see Figure 15). Furthermore, adopting EVs depending on solar energy has the same impact on energy consumption in the 28 EU countries 0.19 (kwh/km) (see Figure 16). Utilizing solar energy shows a significant difference in energy consumption, the score registered for the 28 EU countries using solar energy is around half the minimum score registered in using mixed-sources energy.

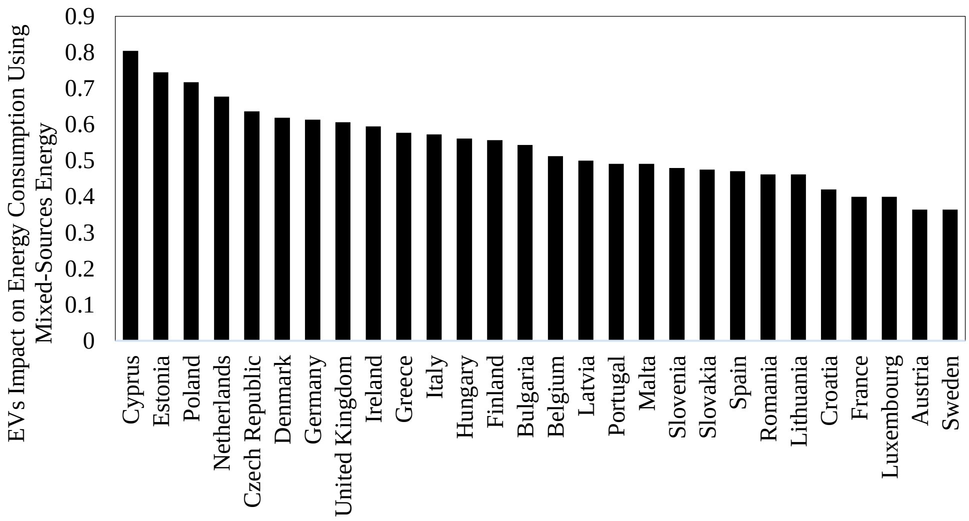

Figure 15. EVs impact on energy consumption using mixed-sources of energy.

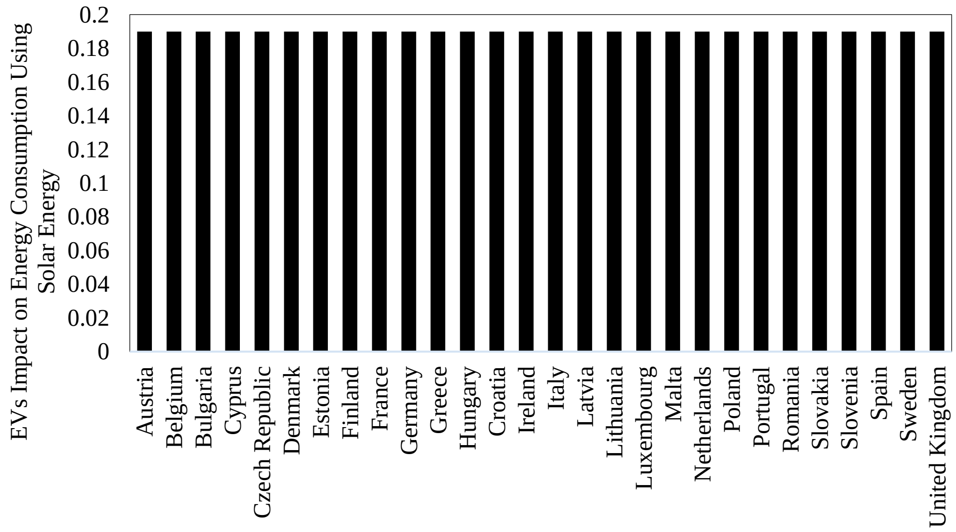

Figure 16. EVs impact on energy consumption using solar energy.

4.4 Contribution to GDP

The average price of generating electricity from mixed- sources and solar energy was calculated for each EU country by collecting data from the world meter database representing each type of energy source's cost. The contribution to GDP represents the electricity price and measured with the $ unit.

In using mixed-source energy, Germany has the highest contribution to GDP, which equals 0.344, the second-highest score is 0.325 for Denmark, where the lowest scores are 0.12, and 0.11 for Lithuania and Bulgaria in order. Figure 17 shows the contribution to GDP recorded for each country while using mixed-sources energy.

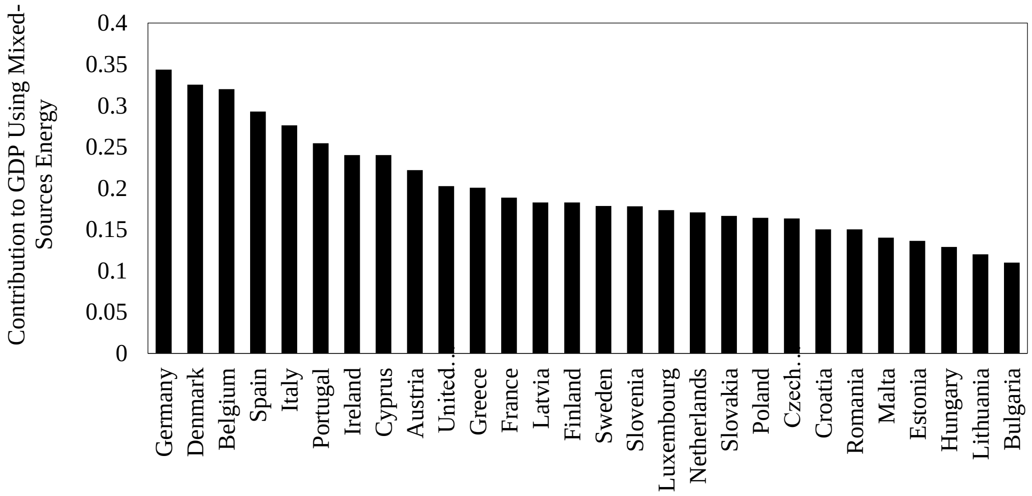

Figure 17. Contribution to GDP using mixed-sources energy.

In the second case, using solar energy to generate electricity, data collected from the world meter database to study how much this process costs the EU countries. Figure 18 shows the contribution to GDP while using solar energy. Austria has the maximum contribution to GDP equals 0.048, followed by Slovenia 0.047. the minimum contribution to GDP recorded are 0.0278 and 0.024 for Greece and Cyprus, respectively.

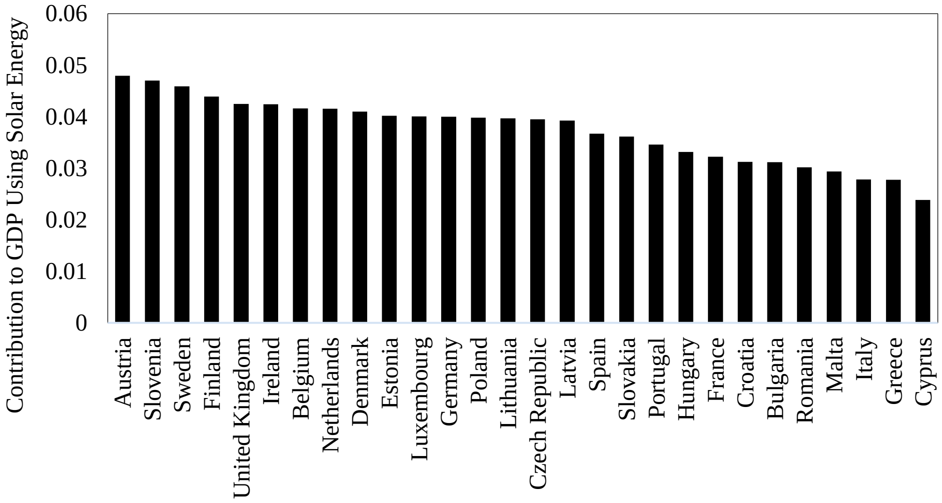

Figure 18. Contribution to GDP using solar energy.

4.5 Efficiency Results and Ranking

The efficiency has a direct relationship between the selected environmental and economic indicators. After analyzing the performance of the 28 EU countries from the environmental perspective, and the contribution to GDP from the economic side, the DEA model, was conducted to evaluate the performance efficiency by relating the economic and environmental data. Scores presented using a scale from 0 to 1, where 0 is the lowest efficiency, and one is the highest. Found that Belgium, Czech Republic, Finland, and Sweden have the highest efficiency score equals 1, using mixed-sources energy. Portugal, Greece, Denmark, and Bulgaria have the lowest efficiency scores 0.388, 0.381, 0.329, and 0.325, respectively. Figure 19 shows the 28 EU countries' efficiency scores using the mixed-sources energy, in descending order.

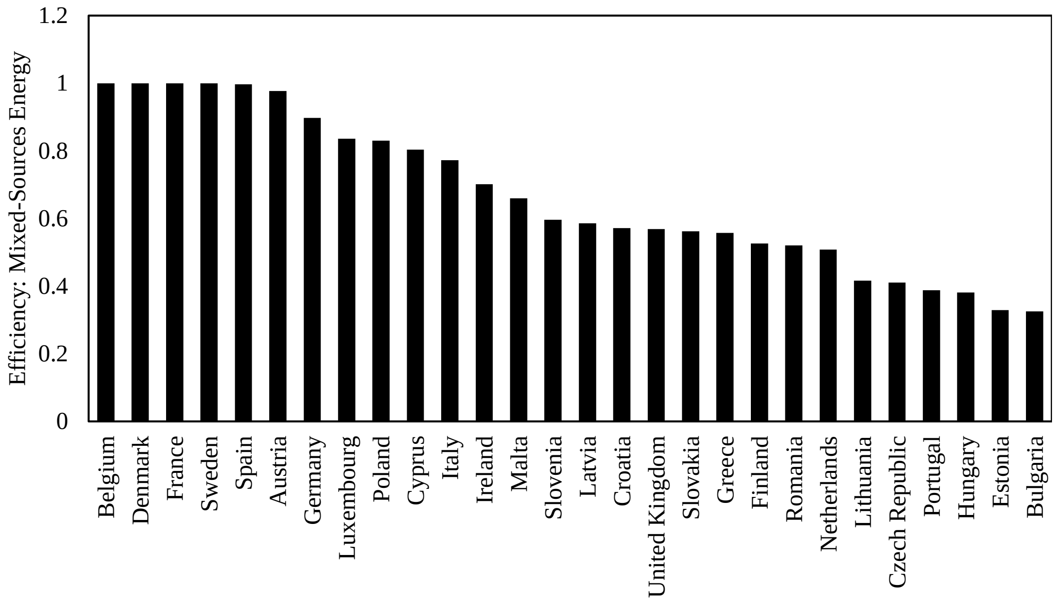

Figure 19. Efficiency scores: Using mixed-sources energy.

Boxplot chart helps present the spread of the dataset on a specific scale and shows the mean value and boundary values. Then it is easy to allocate the dataset in groups. Here a boxplot was used to categorize the EU countries into low efficiency, medium efficiency, and high efficiency. Figure 20 categorizes the countries into low, medium, and high-efficiency groups. From 0 to 0.516, the low range, from 0.516 to 0.859, is the medium range, and the high range falls between 0.859 and 1. Table 10 shows the list of countries under each group.

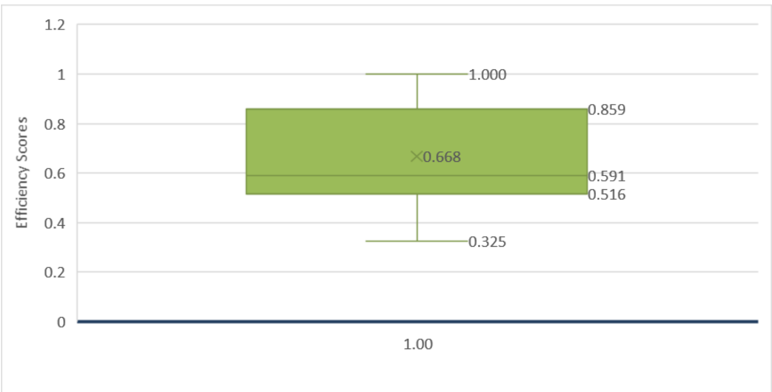

Figure 20. Boxplot of efficiency scores: Using mixed-sources energy.

Table 10. Efficiency Categorization of EU countries Using Mixed-Sources Energy

High Efficiency	Medium Efficiency	Low Efficiency
Belgium	Luxembourg	Netherland
Denmark	Poland	Lithuania
France	Cyprus	Czech Republic
Sweden	Italy	Portugal
Spain	Ireland	Hungary
Austria	Malta	Estonia
Germany	Slovenia	Bulgaria
	Latvia	
	Croatia	
	United Kingdom	
	Slovakia	
	Greece	
	Finland	
	Romania	

Adopting EVs using solar energy, DEA evaluation resulted that Austria has the best efficiency equals 1, followed by Slovenia 0.98, Sweden 0.957, and Estonia 0.915. Oppositely, Malta, Italy, Germany, and Croatia scored the lowest efficiencies, 0.613, 0.58, 0.579, and 0.497 sequentially. Figure 21 shows the 28 EU countries' efficiency scores from highest to lowest using solar energy.

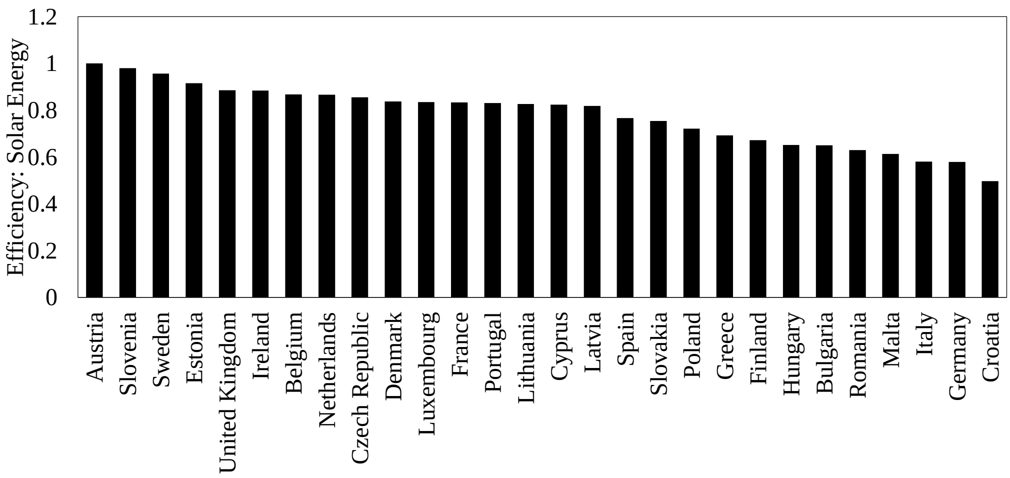

Figure 21. Efficiency scores: Using solar energy

Figure 22 shows the boxplot of efficiency scores of the EU countries when using solar energy. Countries that fall in the range from 0 to 0.657 have low efficiency, countries with scores from 0.657 to 0.868 have medium efficiency, and countries with scores from 0.867 to 1 have high efficiency. Table 11 shows the 28 EU countries distributed into efficiency groups.

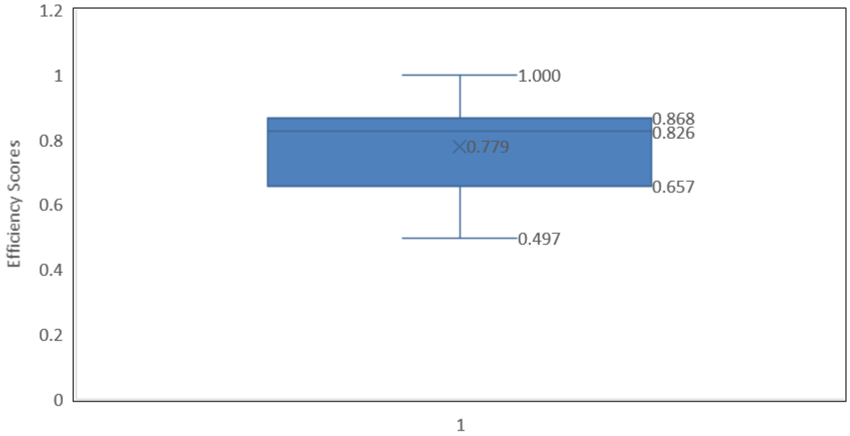

Figure 22. Boxplot of efficiency scores: Using solar energy.

Table 11. Efficiency Categorization of EU countries Using Solar Energy

High Efficiency	Medium Efficiency	Low Efficiency
Austria	Netherland	Hungary
Slovenia	Czech Republic	Bulgaria
Sweden	Denmark	Romania
Estonia	Luxembourg	Malta
United Kingdom	France	Italy
Ireland	Portugal	Germany
Belgium	Lithuania	Croatia
	Cyprus	
	Latvia	
	Spain	
	Slovakia	
	Poland	
	Greece	
	Finland	

4.6 K-Means Clustering

Clustering analysis is an illustrative method that aims to aggregate similar objects to a group; each group is called a cluster. MacQueen is the one who firstly introduces k-mean clustering in 1967 (Yadav & Sharma, 2013). K-mean algorithm employs to classify items according to features into a K number of groups, restricted to numeric data (Teknomo, 2006; Ahmad & Dey, 2007).

K-means uses the mean value of the objects in the same cluster to represent it. To stratify the k-mean algorithm, there are five steps 1) set the number of clusters K 2) setting the centroid value for each K randomly, 3) each object linked to the nearest centroid using Euclidean distance 4) refined the centroid for the new clusters 5) repeat step 3 and 4. Stop the k-means clustering if the objects remain on the cluster. The inputs are the dataset D contains n number of objects, then the output is the desired K clusters (Sharma, 2019).

This section applies the k-means clustering algorithm to aggregate the 28 EU countries into three groups (classes), low-efficiency, medium-efficiency, and high-efficiency. The algorithm was repeated twice, once when using mixed-sources of energy and the second when using solar energy. Also, the k-means clustering is used in both scenarios to aggregate the countries according to the environmental impacts only, not considering the economic indicator. For all of the four cases, the same settings were set, as shown in Table 12.

Table 12. K-means Clustering Algorithm Settings

Iterations	500
Convergence	0.00001
Repetitions	10
Clustering criterion	Determinant(W)
Initial partition	Random
Number of classes (k)	3

For the mixed-sources energy, considering the environmental indicators, only the 28 EU countries distributed among three groups, the high-efficiency group's central country is Austria, for the medium efficiency group Portugal is in the center, where Cyprus is the center of the low-efficiency group. Table 13 shows the central object (country) of each group and its related dimensions.

Table 13. Central Country of Each Group (Mixed-Sources Energy / Environmental Indicators Only)

Group	Impact on Water Consumption	GHG Emissions	Impact on Energy Consumption
1 (Austria)	4.369	27.719	0.364
2 (Portugal)	1.241	63.007	0.491
3 (Cyprus)	0.438	109.328	0.805

Then Table 14 shows each group's results and Table 15 shows the distribution of the 28 EU countries among the groups.

Table 14. Groups Results (Mixed-Sources Energy / Environmental Indicators Only)

Group	High Efficiency	Medium Efficiency	Low Efficiency
Objects	9	11	8
Sum of weights	9	11	8
Within-class variance	151.657	76.390	428.672
Minimum distance to centroid	2.241	0.331	1.112
Average distance to the centroid	10.389	6.435	15.992
Maximum distance to the centroid	20.606	19.143	32.996

Table 15. The Distribution of the 28 EU countries (Mixed-Sources Energy / Environmental Indicators Only)

Group	High Efficiency	Medium Efficiency	Low Efficiency
	Austria	Bulgaria	Cyprus
	Belgium	Denmark	Czech Republic
	Finland	Hungary	Estonia
	France	Croatia	Germany
	Latvia	Italy	Greece
	Lithuania	Malta	Ireland
	Luxembourg	Portugal	Netherlands
	Slovakia	Romania	Poland
	Sweden	Slovenia	
		Spain	
		United Kingdom	

Figure 23 shows the profile plot, which indicates the 28 EU countries' marginal mean at one indicator level.

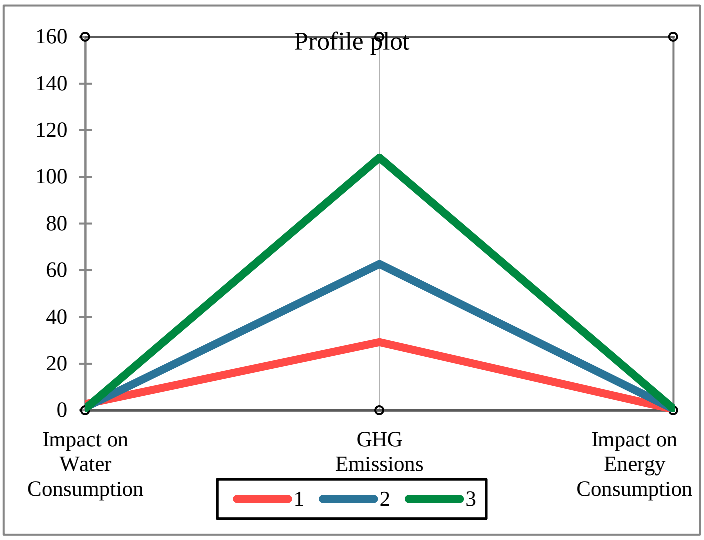

Figure 23. Profile plot (Mixed-Sources Energy / Environmental Indicators Only).

The next k-means algorithm was applied to aggregate the 28 EU countries according to the total efficiency scores, including the economic indicator of GDP contribution. The group centers kept the same, and each country remained in its group as Table 14 & Table 15. Where the profile plot of the total efficiency scores shown in Figure 24.

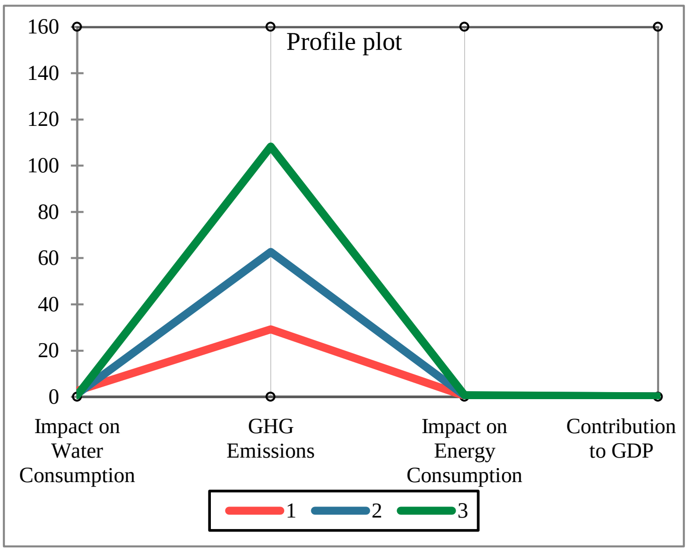

Figure 24. Profile plot (Mixed-Sources Energy / Total Efficiency Scores).

The k-means clustering was applied to aggregate the 28 EU countries using solar energy; the first run included the environmental indicators only. The central country of each group and its related dimensions are shown in Table 16. Belgium is the center of the high-efficiency group, Malta the center of the medium efficiency group, and Slovakia is the center of the low-efficiency group.

Table 16. Central Country of Each Group (Solar Energy / Environmental Indicators Only)

Group	Impact on Water Consumption	GHG Emissions	Impact on Energy Consumption
1 (Belgium)	0.100	0.150	0.190
2 (Malta)	0.140	0.210	0.190
3 (Slovakia)	0.110	0.170	0.190

Then Table 17 shows each group's results and Table 18 shows the distribution of the 28 EU countries among the groups.

Table 17. Groups Results (Solar Energy / Environmental Indicators Only)

Group	High Efficiency	Medium Efficiency	Low Efficiency
Objects	16	10	2
Sum of weights	16	10	2
Within-class variance	0.000	0.001	0.000
Minimum distance to centroid	0.004	0.004	0.000
Average distance to the centroid	0.009	0.021	0.000
Maximum distance to the centroid	0.019	0.062	0.000

Table 18. The Distribution of the 28 EU countries (Solar Energy / Environmental Indicators Only)

Group	High Efficiency	Medium Efficiency	Low Efficiency
	Austria	Bulgaria	Slovakia
	Belgium	Cyprus	Spain
	Czech Republic	France	
	Denmark	Greece	
	Estonia	Hungary	
	Finland	Croatia	
	Germany	Italy	
	Ireland	Malta	
	Latvia	Portugal	
	Lithuania	Romania	
	Luxembourg		
	Netherlands		
	Poland		
	Slovenia		
	Sweden		
	United Kingdom		

The marginal mean of each environmental indicator while using solar energy is represented as a profile plot in Figure 25.

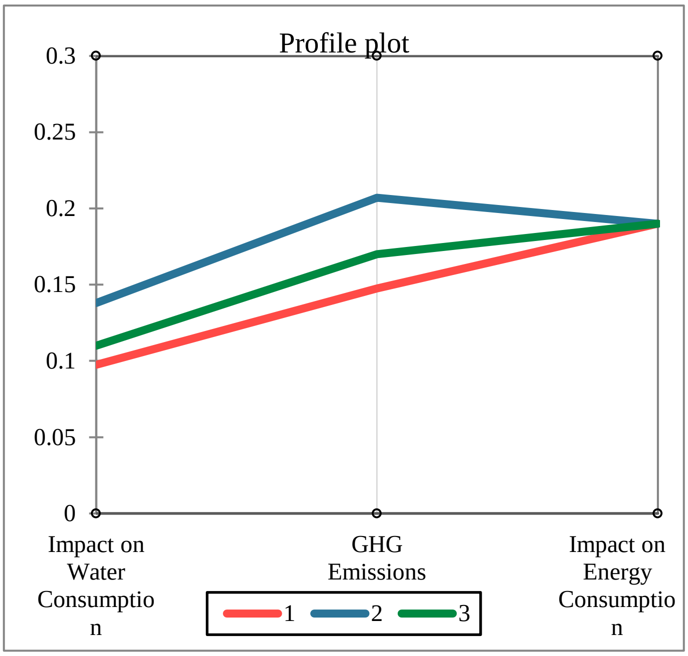

Figure 25: Profile plot (Solar Energy / Environmental Indicators Only).

The last k-means clustering run was for the total efficiency scores considering the economic indicator while using solar energy. In this case, the results differed from the mixed-solar energy, and the economic indicator showed a significant effect in changing the central country of each group see Table 19.

Table 19. Central Country of Each Group (Solar Energy / Total Efficiency Scores)

Group	Impact on Water Consumption	GHG Emissions	Impact on Energy Consumption	Contribution to GDP
1 (Ireland)	0.100	0.150	0.190	0.042
2 (Malta)	0.140	0.210	0.190	0.029
3 (Spain)	0.110	0.170	0.190	0.037

The 28 countries were distributed into efficiency groups the group results are shown in Table 20 and the distribution of the countries shown in Table 21.

Table 20. Groups Results (Solar Energy / Total Efficiency Scores)

Group	High Efficiency	Medium Efficiency	Low Efficiency
Objects	16	10	2
Sum of weights	16	10	2
Within-class variance	0.000	0.001	0.000
Minimum distance to centroid	0.004	0.004	0.000
Average distance to the centroid	0.009	0.021	0.000
Maximum distance to the centroid	0.020	0.062	0.000

Table 21. The Distribution of the 28 EU countries (Solar Energy / Total Efficiency Scores)

Group	High Efficiency	Medium Efficiency	Low Efficiency
	Austria	Bulgaria	Slovakia
	Belgium	Cyprus	Spain
	Czech Republic	France	
	Denmark	Greece	
	Estonia	Hungary	
	Finland	Croatia	
	Germany	Italy	
	Ireland	Malta	
	Latvia	Portugal	
	Lithuania	Romania	
	Luxembourg		
	Netherlands		
	Poland		
	Slovenia		
	Sweden		
	United Kingdom		

Lastly, Figure 26 shows the profile plot of the marginal mean of each indicator.

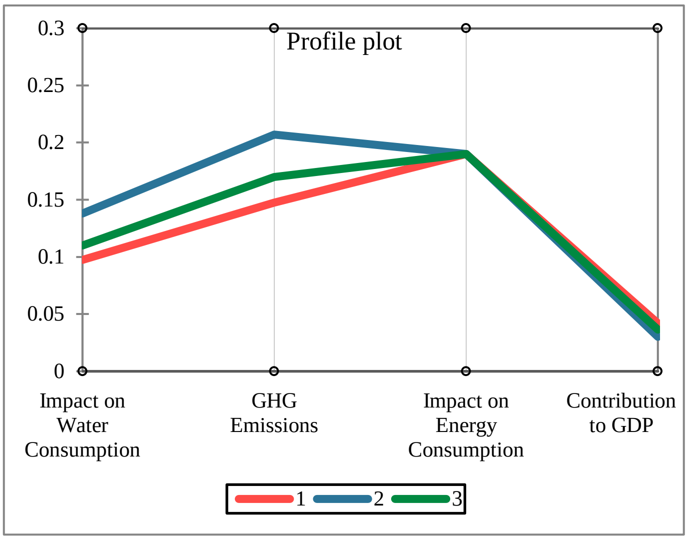

Figure 26. Profile plot (Solar Energy / Total Efficiency Scores).

At the end of the k-means clustering algorithm, it is clear how using different energy sources could change the efficiency of adopting EVs. Some countries were in the low-efficiency group in using mixed-source energy, such as Germany and Estonia, then shifted to the high-efficiency group using solar energy.

For a clearer view of the efficiency scores obtained by each country, the heat map of Europe was used for both scenarios. Figure 27 shows the efficiency scale while using mixed-sources energy. And Figure 28 shows the efficiency scale when using solar energy.

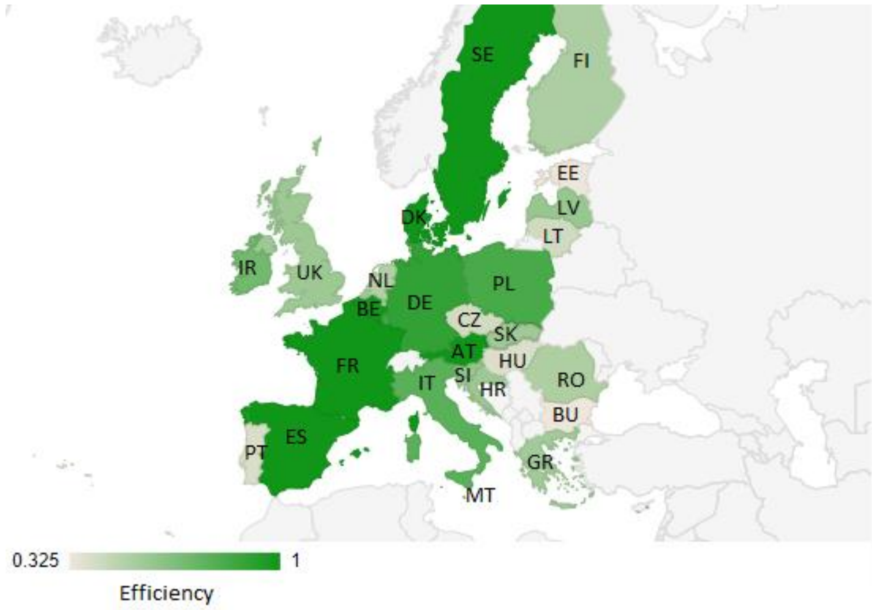

Figure 27. Efficiency scores using mixed-sources energy.

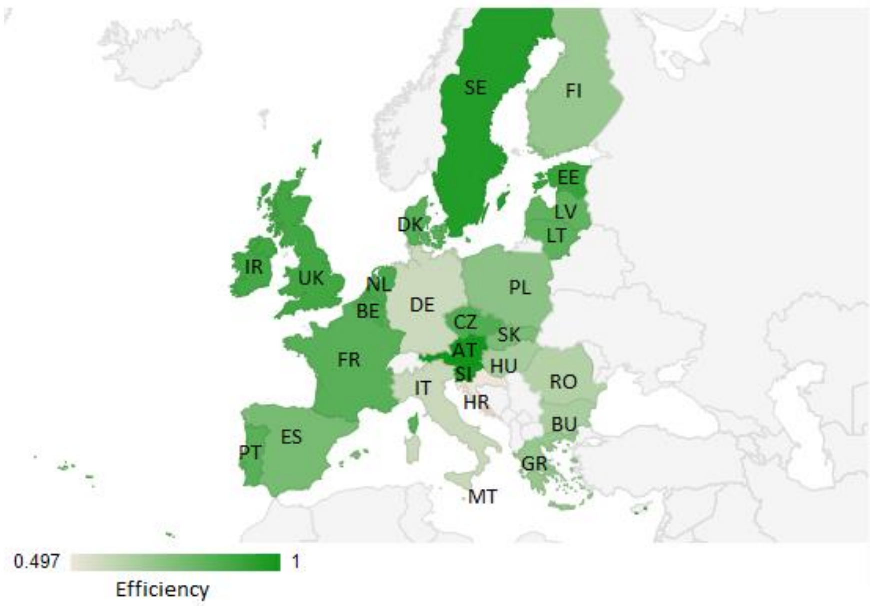

Figure 28. Efficiency scores using solar energy

4.7 Efficiency Comparison Using T-Test Tool

As the efficiency evaluated for each of the 28 EU countries using the DEA technique, considering two types of energy sources, a comparison is needed to report which energy source was more efficient in each county.

In 1908 William Sealy Gosset introduced the t-test as a statistical analysis tool, which is also called the students' test (Kim, 2015)

The t-tests are popular in the statistics field, and there is more than one type of t-tests, researchers could choose the appropriate t-test according to the available samples (Xu, et al., 2017). The independent two samples t-test tool was employed to conduct the comparison, which computes the difference between the two sample means.

The 28 countries efficiency scores based on the usage of mixed-sources energy (Table 9) with (M = 0.67, SD = 0.23) compared to the 28 efficiency scores obtained after the solar energy usage (Table 10) with (M = 0.78, SD = 0.13), where M is the mean value and SD is the standard deviation. The degree of freedom (df) indicates the number of values is free to vary without breaking the constraints for both sample groups df 54. The difference scores calculations are shown in Table 22, and the significance level = 0.05

Table 22. Tow Independent Samples t-test Calculations

Scenario	Mixed-Sources Energy (Case 1)	Solar Energy (Case 2)
Sample Size (N)	28	28
Mean (M)	0.67	0.78
Degrees of freedom (df) = $(N_1 - 1) + (N_2 - 1)$	27+27 = 54	27+27 = 54
Sum of Squared Difference (SS) = $(X\text{-}M)^2$	1.43	0.47
$S^2 = \boldsymbol{SS}/(\boldsymbol{N-1})$	0.05	0.02

t-value calculations:

S_P^2 = ((df$_1$/(df$_1$ + df$_2$)) * S_1^2) + ((df$_2$/(df$_2$ + df$_2$)) * S_2^2) = ((27/54) * 0.05) + ((27/54) * 0.02) = 0.04

S_{M1}^2 = $S_P^2 / \boldsymbol{N_1}$ = 0.04/28 = 0.00143

S_{M2}^2= $S_P^2 / \boldsymbol{N_2}$ = 0.04/28 = 0.00143

$$t = (M_1 - M_2) \Big/ \sqrt{(S_{M1}^2\ M_1\ + S_{M2}^2\ M_2)} = -0.11/\ 0.0472313 = -2.33$$

If the negative sign appeared due to $M_2 > M_1$. Then negative t-value tells the direction of the difference in sample means.

Beers, 2020 stated that 'The p-value is the probability of obtaining results at least as extreme as the observed results of a statistical hypothesis test assuming that the null hypothesis is correct.'

The calculated p-value for the two datasets is p = .0155, which is less than .05, which means the result is significant. The smaller p-value indicates the better alternative, then using solar energy is more efficient than using mixed-sources energy.

Figure 29 shows the average efficiency scores and the difference between the efficiencies in both scenarios and error bars between the obtained average and the standard deviation.

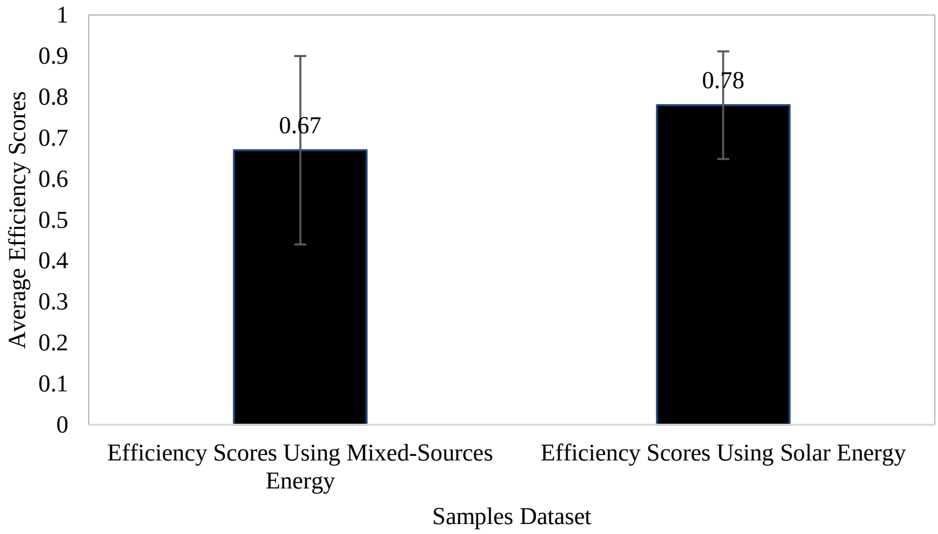

Figure 29. Average efficiency scores.

Figure 30 shows the efficiency scores for each of the 28 EU countries while using mixed-sources energy and solar energy, in addition to the error bars between the efficiency scores and the difference (X-M), where X is the efficiency score and M is the mean value.

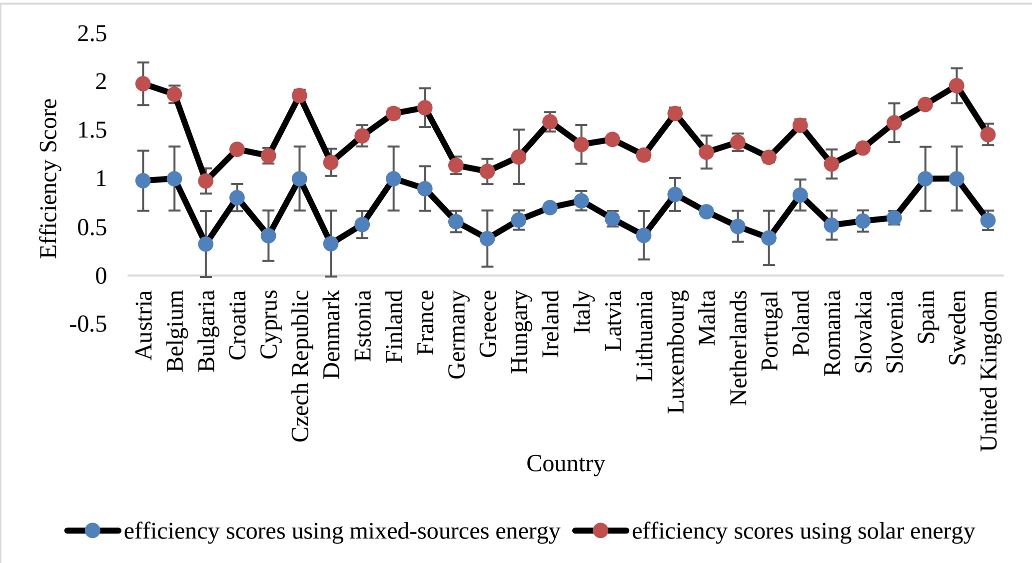

Figure 30. Efficiency scores for 28 EU countries using mixed- sources and solar energy.

CHAPTER 5: CONCLUSION AND FUTURE WORK

This research aimed to evaluate EVs' adoption in 28 EU countries by applying a DEA input-oriented single-stage model to evaluate EVs' efficiency. DEA model was selected because it fits the evaluation of environmental indicators and efficiency assessment. Two scenarios have been considered. The first one was adopting EVs using mixed-sources energy; the second scenario was adopting EVs using solar energy. The three environmental indicators were; water consumption, GHG emissions, and energy consumption; the economic indicator was the Contribution to GDP. Efficiency scores were given on a scale from 0 to 1. The maximum efficiency score obtained in using mixed-sources energy was 1, and it appeared for four countries, namely Belgium, Czech Republic, Finland, and Sweden while the minimum efficiency score of 0.325 was for Bulgaria.

On the other hand, the best efficiency score was 1 for Austria while using solar energy, and the lowest efficiency scored by Croatia is 0.497. Comparing the two energy types and the EU countries' efficiency scorees, this research concludes that adopting EVs using mixed-sources energy has higher environmental impacts than using solar energy to generate electricity. However, the overall efficiency scores obtained show that four countries hit the maximum possible efficiency in using mixed-source energy while only Austria scores 1 in solar energy.

Later in this study, the k-means clustering algorithm was employed to group the 28 countries into three groups: high efficiency, medium efficiency, and low efficiency. In addition, it was found that using mixed-source energy, Austria, Belgium, and Finland are in the high-efficiency group. Countries that fall on the medium efficiency group are Bulgaria, Denmark, and Hungary. The remaining countries on the low-efficiency group are Cyprus, Czech Republic, Estonia, Germany, Greece, Ireland, Netherlands, and

Poland.

In the second scenario where solar energy is used, the k-clustering algorithm aggregates the 28 EU countries. The high-efficiency group contains Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, Germany, Ireland, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Slovenia, Sweden, and the United Kingdom. Bulgaria, Cyprus, France, Greece, Hungary, Croatia, Italy, Malta, Portugal, and Romania are members of the medium efficiency group, where only Slovakia and Spain are in the low-efficiency group.

Comparing the obtained results from the box plot chart with the k-means clustering algorithm results found differences in the countries' distribution; these differences occur because each technique aggregates the countries according to a different perspective.

Future work could consider many other environmental and economic indicators, collecting the most recent data and considering more countries from different regions. Furthermore, considering different EV types such as PHEV, with the full life cycle, and not to be limited to the operational phase. Moreover, the opportunity to apply another assessment approach than DEA, e.g., LCA. Sustainability also includes a social dimension, which could be added to the study in the future to have a full sustainability assessment of adopting EVs.

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