A Frontier Based Eco-Efficiency Assessment of Electric Vehicles: The Case of European Union Countries Using Mixed and Renewable Sources of Energy

Adeeb A. Kutty, Rania Al-Jondob, Galal M. Abdella and Tarek El-Mekkawy
Mechanical and Industrial Engineering Department
College of Engineering, Qatar University
Doha, Qatar
akutty@qu.edu.qa , ra1800222@student.qu.edu.qa , gmg5005@qu.edu.qa , tmekkawy@qu.edu.qa

Abstract

Electric vehicles (EVs) are seen as a promising solution for creating more efficient and sustainable transportation systems. European Union (EU) members show a strong interest in implementing EVs, and the governments support the concept by offering facilities to the buyers. Although electric vehicles can be operated with nonpolluting fuels, such as natural gas, fuel cells are more efficient. Creating electricity can affect the environment and the economy. Three environmental features (consumption of water, GHG emissions, and energy consumption, plus GDP's contribution to EU gross domestic product) were analyzed for 28 EU member states to measure electric vehicle efficiency. In one of the DEA models, an input-oriented method was employed to compute the efficiency scores. The k-means clustering algorithm defined the high, medium, and low-efficiency groups. Even more so, the total efficiency scores in this study show that using solar energy outperforms mixed-source energy sources was found to be more efficient.

Keywords

Data Envelopment Analysis, Eco-efficiency, Electric Vehicle, Sustainable Transport System.

1. Introduction

The idea of carbon-neutral mobility has prompted countries worldwide to switch from fossil-fueled transportation to more efficient carbon-neutral electric transportation (Casals et al., 2016; Abdella et al., 2016). Electric vehicles are proposed as a long-term solution to the harmful effects of traditional transportation, especially on the environment (Cole & Wright, 2003; Sikes et al., 2009). In member states such as the European Union (EU), where EV use rose to 3.6 percent in 2019 from 2.5 percent the year before, with approximately 1.8 million total EV registrations to date, electromobility has been a priority (Onat et al., 2021). By 2020, the EU has set a target of reducing CO_2 emissions to 95 g.CO2/km of capacity (Kutty et al., 2020). The EU's guidelines for greenhouse gas (GHG) emission reduction pathways have aided in introducing electric vehicles (Wappelhorst et al., 2020). Electric vehicle usage has grown due to manufacturers' and consumers' strong confidence in zero-emission mobility options (Onat et al., 2021). The quest for long-term solutions to pressing environmental issues has also paved the way for EV adoption. Despite cutting low carbon emissions, EV adoption holds possible reduction in human health, resource depletion, and ecological system damage across the life cycle, thus helping harmonize EV adoption with the sustainable development agenda 2030 (Kutty et al., 2020b; Alsarayreh et al., 2020). The critical factors that hold a significant effect on the climate, according to studies conducted by Hawkins et al. (2012), Nordelof et al. (2014), Onat et al. (2018), and Elhamoud and Kutty (2021), are; energy use and the global warming potential (GWP).

The European Union (EU) plans to have environmentally friendly fuels on the market by 2010 and ten percent renewable energy in the transportation sector by 2020. By a factor of 2.5, using EV increases the probability of meeting the targets (Onat et al., 2021). The EU countries decided in 2008 to set a limit of 40 g/m3/year for NO_2 and PM10. More than 6% of the population was affected by NO_2 annual concentrations that exceeded 40 g in 2010. In general, an electric vehicle consumes half as much energy as a conventional vehicle. Although electric vehicle technology has reduced GHG emissions, it is still unclear how each county used to generate electricity. The use of nuclear, coal and renewable energy in Germany decreases the environmental impact of electric vehicle charging. On the other hand,

© IEOM Society International

Poland has a high emission rate due to its dependence on coal power, which has contributed to an increase in the demand for electric vehicles, affecting the energy future (Helms et al., 2015).

The efficiency of implementing BEVs in 28 EU states is assessed in this study using Data Envelopment Analysis (DEA). DEA takes into account the operational phase of the life cycle. The results of the DEA study were modeled using data visualization software to compare the performance of mixed-source energy and solar energy adoption. This study focuses on the efficiency of two different energy sources and compares each country's efficiency in both cases. The aim is to determine which type of energy is more effective in EV adoption and how efficient each country uses it to electric power vehicles in different EU countries. The study will evaluate the eco-efficiency of EV adoption in 28 countries, taking three environmental indicators and one economic indicator across both mixed and renewable sources of electricity generation.

2. Measuring Eco-efficiency Performance

2.1 Data description

This study aims to determine the efficiency of BEVs in the operational process when they are powered by a combination of mixed-energy and solar energy sources. Three environmental indicators were chosen, as well as one economic indicator. There are 1) water use, 2) greenhouse gas emissions, and 3) electricity use. The contribution to GDP is selected to reflect the economic value-added. The electricity data for the 28 EU countries was produced using databases from Eurostat, World Energy Statistics, and Electricity Information. The brand "Nissan Leaf" is used to measure the effects of electric vehicles, taking into account their energy consumption in kilowatt-hours (30 kWh per 100 miles); see Table 1.

Table 1. Indicators used for the eco-efficiency analysis

Category	Indicator	Unit
	GHG Emissions	g CO_2-eq /kWh
Environmental	Energy Consumption	kWh/kWh
	Water Consumption	L/kWh
Economic	Contribution to GDP	US$

2.2 Single-stage DEA model

In this section, an input-oriented single-stage DEA model was used under mixed-source electricity and solar energy to evaluate the EV eco-efficiency in each of the 28 EU countries. The performance of each country was calculated using the output-to-input ratio. 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 (Kucukvar et al., 2017; Kucukvar et al., 2020). The main goal of the DEA model is to optimize the inputs because the better the transportation system is, the less water, electricity, and GHG emissions are generated. As in Equation 2, the output over input ratio must be less than or equal to 1, which means the number of the three input DMUs (denominator) must be less than or equal to the output (numerator). The weight coefficients are the subject of Equations 3 and 4. Each indicator is assigned a weight based on its significance. On the other hand, decision variables are nonnegative, so that weights may be zero or more (Abdella et al., 2021; Abdella et al., 2021a).

Objective Function:

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

Subject to

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

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

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

where *n* represents the number of inputs, *k* represents the number of output (DMUs), y_k represents the amount of output produced by the DMU k, x_{ik} represents the amount of input i used by the DMU k, and u and v_i represent the output multiplier and input multiplier, respectively.

The selected environmental and economic indicators have a direct relationship with the eco-efficiency performance. The DEA model compared economic and environmental data to assess eco-environmental efficiency. Scores are given on a scale of 0 to 1, with 0 representing the least efficient and 1 representing the most efficient. Figure 1 shows the DEA efficiency results for each of the 28 EU countries, following the data relating to mixed energy sources. The eco-efficiency of solar energy was then assessed using another DEA model. Figure 2 depicts the eco-efficiency ratings of 28 EU countries regarding renewable energy sources used in the electricity mix.

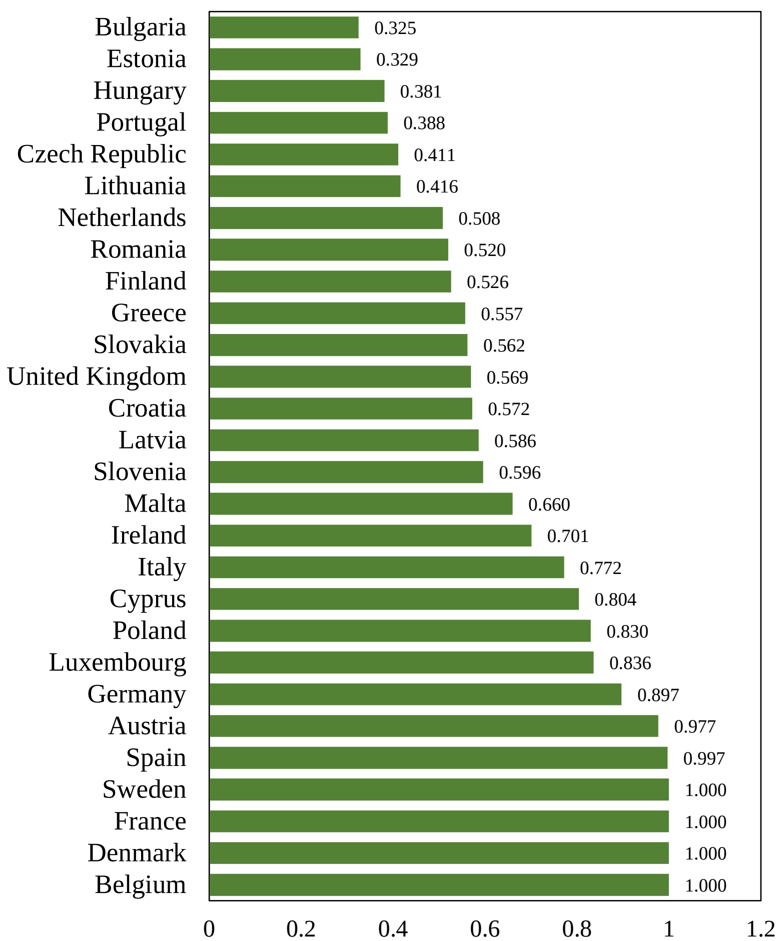

Figure 1. EVs-eco-efficiency scores using mixed-sources of energy

Using mixed-sources electricity, the highest efficiency score equals 1 in Belgium, Czech Republic, Finland, and Sweden. The lowest efficiency ratings are 0.388, 0.381, 0.329, and 0.325, respectively, for Portugal, Greece, Denmark, and Bulgaria. When it comes to solar-powered electric vehicles, the DEA found Austria has the highest efficiency at 1, followed by Slovenia at 0.98, Sweden at 0.957, and Estonia at 0.915. On the other hand, Malta, Italy, Germany, and Croatia had the lowest efficiencies, with 0.613, 0.58, 0.579, and 0.497.

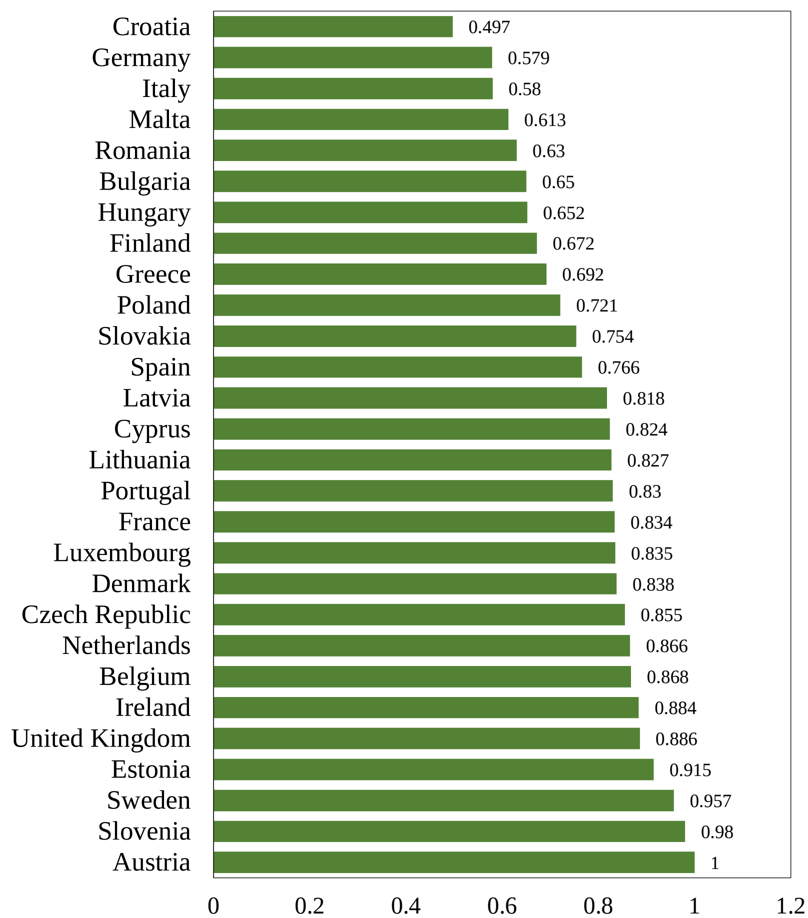

Figure 2. EVs-eco-efficiency scores using solar energy.

3.3 K-means Performance Clustering

The 28 EU countries are divided into three groups (classes) using K-means clustering: low-efficiency, medium-efficiency, and high-efficiency. The algorithm was run twice, once with mixed-source energy and again with solar energy. In addition, in both cases, k-means clustering is used to aggregate the countries based on the eco-environmental predictors and solely on the environmental indicators. The same settings were used in all situations; see Table 2.

Table 2. K-means clustering inputs

Parameters	Value
#Iterations	500
#Repetitions	10
Clustering criterion	Determinant (W)
Initial partition method	Random
Number of classes (k)	3

The 28 EU countries were then aggregated using the k-means algorithm based on their total efficiency ratings, including the economic measure of GDP contribution. Considering the environmental indicators, the 28 EU states were distributed among three groups for the mixed-energy source. Austria is the high-efficiency group's center, Portugal is the medium-efficiency group's center, and Cyprus is the low-efficiency group's center. For total efficiency scores when using mixed-source energy, considering economic indicators, the group centers remained the same, and each nation was placed in the same group it had been in previously (Figure 3-a).

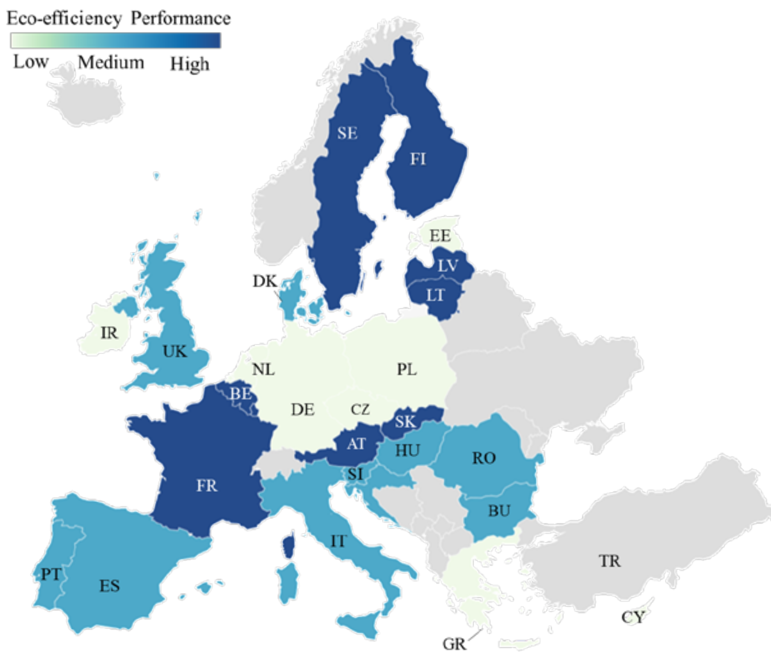

Figure 3-a Heat map of EVs eco-efficiency performance groups using mixed-sources energy

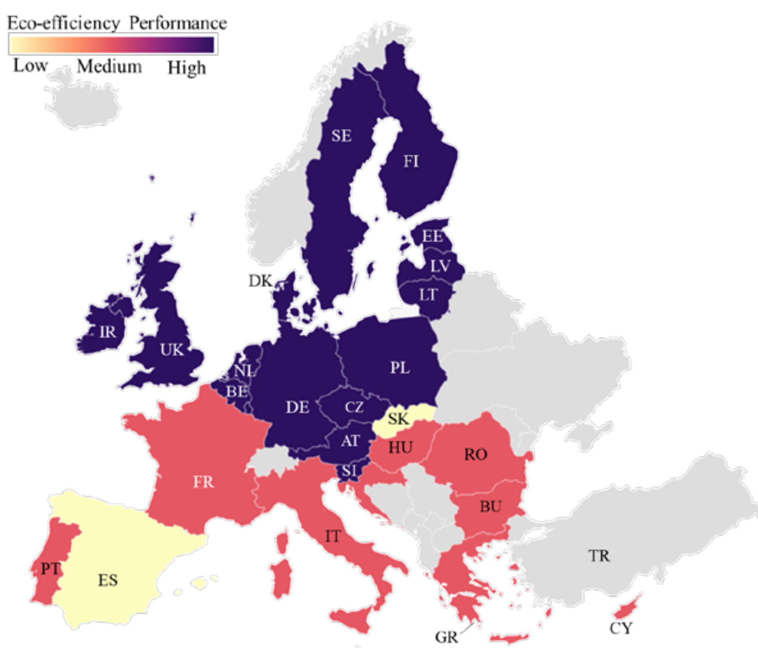

Figure 3-c Heat map of EVs eco-efficiency performance groups using solar energy when accounting for total efficiency scores.

The 28 EU countries that use solar energy were then aggregated using k-means clustering; the first run only included environmental indicators. Belgium is the high-efficiency group's center, Malta is the medium-efficiency group's center, and Slovakia is the low-efficiency group's center. The most recent k-means clustering run was for total efficiency scores when using solar energy, considering economic indicators. In this case, the findings were different from mixed-solar energy with environmental indicators alone, where the economic predictor had a major impact on changing each group's central unit. Ireland is the high-efficiency group's center, Malta is the medium-efficiency group's center, and Spain is the low-efficiency group's center when accounting for total efficiency scores, including the economic indicator of GDP contribution (Figure 3-b). At the end of the k-means clustering process, it is clear how different energy sources will affect the efficiency of EV adoption. When it came to mixed-source electricity, some nations, such as Germany and Estonia, were in the low-efficiency category, but they fall under the high-efficiency group when it came to solar energy. The heat map of Europe was used for both scenarios to provide a clearer view of the efficiency scores obtained by each nation. Figure 3a depicts the performance scale when mixed-source energy is used. Figure 3b depicts the performance scale when solar energy is used.

3.4 Comparing eco-efficiency of two energy scenarios using t-test

After the efficiency of each of the 28 EU countries is assessed using the DEA method and two types of energy sources are considered, a comparison is needed to determine which energy source is more efficient in each country. The comparison is carried out using the independent two-sample t-test tool, which computes the difference between the two-sample definitions. The 28 countries' efficiency scores after using mixed-source energy (M = 0.67, SD = 0.23) were compared to the 28 countries' efficiency scores after using solar energy (M = 0.78, SD = 0.13), where M represents the mean value and SD represents the standard deviation. For both sample sets, the degree of freedom (df) shows how much the number of values will differ without violating the constraints df 54. Table 3 shows the difference score estimates, with a significant amount of 0.05.

Table 3. Test statistics

Statistic	Solar Energy	Mixed-sources energy
Observations	28	28
Average	0.781	0.672
Degrees of freedom	54	54
Variance	0.020	0.051

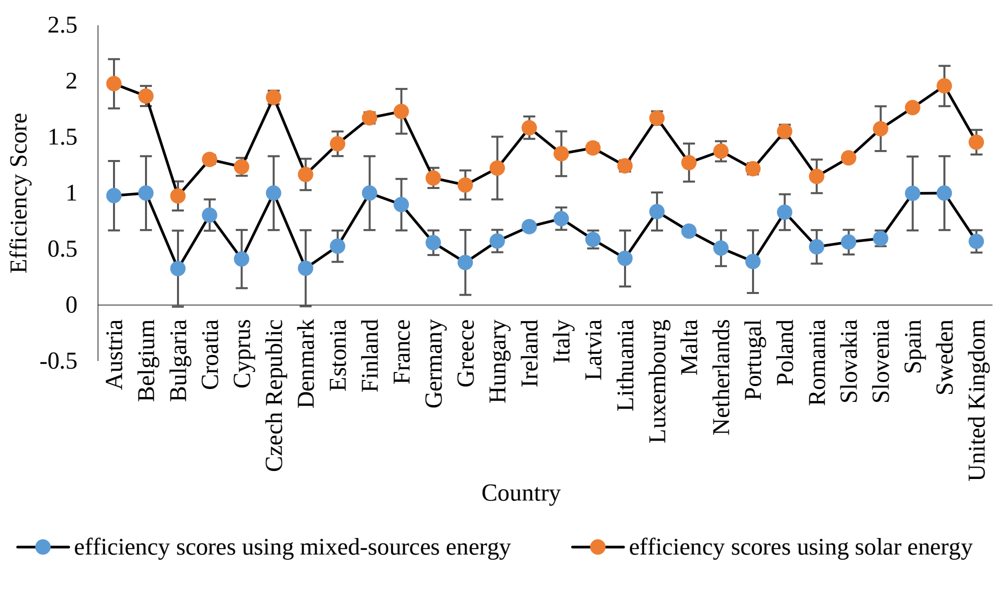

Figure 4: Efficiency scores for 28 EU countries using mixed- sources and solar energy

For the two datasets, the estimated p-value is p =.0155, which is less than.05, indicating that the result is important. The lower the p-value, the better the alternative; in this case, solar energy is more effective than mixed-sources energy. Figure 4 depicts the efficiency scores for each of the 28 EU countries using mixed-source electricity and solar energy and the error bars between the efficiency scores and the difference (X-M), where X represents the efficiency score and M represents the mean value.

For the two datasets, the estimated p-value is p =.0155, which is less than.05, indicating that the result is important. The lower the p-value, the better the alternative; in this case, solar energy is more effective than mixed-sources energy. Figure 4 depicts the efficiency scores for each of the 28 EU countries using mixed-source electricity and solar energy and the error bars between the efficiency scores and the difference (X-M), where X represents the efficiency score and M represents the mean value.

4. Discussion and Remarks

This study aimed to assess EV adoption in 28 EU countries using a DEA input-oriented single-stage model to assess EV performance. The DEA model was chosen because it is well-suited for evaluating environmental indicators and determining performance. There have been two scenarios considered. The first example involved using mixed-source electricity to electric power vehicles, while the second involved using solar energy to electric power vehicles. Water intake, GHG pollution, and energy consumption were the three environmental indicators, while Contribution to GDP was the economic indicator. On a scale of 0 to 1, efficiency scores were assigned. When using mixed-sources electricity, the highest efficiency score was 1, which was achieved by four countries: Belgium, Czech Republic, Finland, and Sweden, with Bulgaria having the lowest efficiency score of 0.325.

On the other hand, Austria had the highest efficiency score of 1 when using solar energy, while Croatia had the lowest efficiency score of 0.497. This study concludes that implementing EVs using mixed-source energy has higher environmental impacts than using solar energy to produce electricity, after comparing the two energy forms and the performance scores of EU countries. However, the overall performance scores reveal that four countries achieved the highest possible efficiency while using mixed-source electricity, while only Austria received a 1 for solar energy. The k-means clustering algorithm was used later in this analysis to divide the 28 countries into three categories: high performance, medium efficiency, and low efficiency. Furthermore, Austria, Belgium, and Finland were discovered to be in the high-efficiency category when using mixed-source electricity. Bulgaria, Denmark, and Hungary are among the countries with a medium efficiency level. Cyprus, Czech Republic, Estonia, Germany, Greece, Ireland, the Netherlands, and Poland round out the low-efficiency party.

Future work could include a wide range of environmental and economic indicators and the most up-to-date data, and a larger number of countries from various regions. Furthermore, different EV forms, such as PHEV, should be considered during their entire life cycle, not just during the operational period. Furthermore, the choice to use a different evaluation method than DEA, such as PCA, is also advised (see: Park et al., 2015). Similarly, Life cycle approaches can be used to identify the impact generated on the per km traveled across each indicator category and then understand the efficiency performance. To better understand various life cycle integrated approaches, the readers can refer (Kutty and Abdella, 2020; Elhmoud and Kutty, 2021). Combinatorial approaches are also well suggested for future research, such as a variable selection approach before DEA when using large data sets (Yang et al., 2012; Abdella et al., 2017; Abdella and Shaaban, 2020) to obtain a two-stage DEA model. Weight restriction helps us identify whether discrimination limits the capacity of the DEA model to bring efficient results compared with the traditional model for the envelopment analysis. Penalized-based weighting approaches are best suggested for weight restriction while running a weighted DEA model for eco-efficiency assessment. To better understand various statistical-based weighting approaches, readers can further refer Abdur-Rouf et al., 2018; Abdella et al., 2019a; Al-Sheeb et al., 2019; Abdella et al., 2020; Abdella et al., 2020a; and Kutty et al., 2020a. Expert-based weights can also be assigned to the eco-efficiency indicators to run a fuzzy-weighted DEA model, as shown in Egilmez et al., 2016. Sustainability also requires a social component, which could be applied to the study in the future to include a comprehensive evaluation of the long-term viability of EV adoption.

© IEOM Society International

References

Abdella G. M., Al-Khalifa, K. N., Kim, S., Jeong, M. K., Elsayed, E. A., and Hamouda, A.M.S., Variable Selection-based Multivariate Cumulative Sum Control Chart, Quality and Reliability Engineering International, vol. 33, pp. 565–78, 2017.

Abdella, G. M., and Shaaban, K., Modeling the Impact of Weather Conditions on Pedestrian Injury Counts Using LASSO-Based Poisson Model, *Arabian Journal for Science and Engineering*, pp. 1-12, 2020.

Abdella, G. M., Kim, J., Al-Khalifa, K. N., and Hamouda, A. M. S., Penalized Conway-Maxwell-Poisson regression for modeling dispersed discrete data: The case study of motor vehicle crash frequency, *Safety Science*, vol. 120, pp. 157-63, 2019a.

Abdella, G. M., Kim, J., Al-Khalifa, K. N., and Hamouda, A.M.S., Double EWMA-based polynomial profile monitoring, *International Journal of Quality and Reliability*, vol. 32, pp. 2639-52, 2016.

Abdella, G. M., Kucukvar, M., Onat, N. C., Al-Yafay, H. M., and Bulak, M. E., Sustainability assessment and modeling based on supervised machine learning techniques: The case for food consumption, *Journal of Cleaner Production*, vol. 251, 2020.

Abdella, G. M., Maleki, M. R., Kim, S., Al-Khalifa, K. N., and Hamouda, A. M. S., Phase-I monitoring of high-dimensional covariance matrix using an adaptive thresholding LASSO rule. *Computers & Industrial Engineering*, pp. 106465, 2020a.

Abdur-Rouf K. B., Abdella, G. M., Al-Khalifa, K. N., and Alhajyaseen, W., Ridge penalization-based generalized linear model (GzLM) for predicting risky-driving index, *In the Proceedings of the International Conference on Industrial Engineering and Operations Management*, Washington DC, USA pp. 1462-73, 2018.

Alsarayreh, M. M., AlSuwaidi, M. F., Sharif, R. A., and Kutty, A. A., The Factors Affecting CO_2 Emission in the European Union Countries: A Statistical Approach to Sustainability across the Food Industry, *2020 IEEE 7th International Conference on Industrial Engineering and Applications (ICIEA)*, IEEE, April 16-21, 2020.

Al-Sheeb, B., Abdella, G. M., Hamouda, A. M. S., and Abdulwahed, M. S., Predictive modeling of first-year student performance in engineering education using sequential penalization-based regression, *Journal of Statistical Management Systems*, vol. 22, pp. 31-50, 2019.

Abdella, G. M., Kucukvar, M., Kutty, A. A., Abdelsalam, A. G., Sen, B., Bulak, M. E., & Onat, N. C., A novel approach for developing composite eco-efficiency indicators: The case for US food consumption. *Journal of Cleaner Production*, vol. 299, p.126931, 2021.

Abdella, G. M., Kucukvar, M., Ismail, R., Abdelsalam, A. G., Onat, N. C., & Dawoud, O., A mixed model-based Johnson's relative weights for eco-efficiency assessment: The case for global food consumption. *Environmental Impact Assessment Review*, vol. 89, 106588, 2021a.

Casals, L. C., Martinez-Laserna, E., García, B. A., & Nieto, N. (2016). Sustainability analysis of the electric vehicle use in Europe for CO2 emissions reduction. *Journal of Cleaner Production*, vol. 127, pp. 425-437, 2016.

Cole, L., and Wright, T., Assessing sustainability on Canadian University campuses: development of a campus sustainability assessment framework. Royal Roads University, Vectoria, BC, *Master's Thesis*, 2003.

Egede, P., Dettmer, T., Herrmann, C., and Kara, S., Life Cycle Assessment of Electric Vehicles – A Framework to Consider Influencing Factors. *Procedia CIRP*, 29, 233-238. doi:https://doi.org/10.1016/ j.procir.2015.02.185, 2015.

Elhmoud, E. R., and Kutty, A. A., Sustainability Assessment in Aviation Industry: A Mini-Review on the Tools, Models and Methods of Assessment. *In the Proceedings of the International Conference on Industrial Engineering and Operations Management. Harare, Zimbabwe*, October 20-22, 2021.

Egilmez, G., Gumus, S., Kucukvar, M., and Tatari, O., A fuzzy data envelopment analysis framework for dealing with uncertainty impacts of input–output life cycle assessment models on eco-efficiency assessment, *Journal of cleaner production*, vol. 129, pp. 622-636, 2016.

Hawkins, T. R., Gausen, O. M., and Strømman , A. H., Environmental impacts of hybrid and electric vehicles—a review. The International Journal of Life Cycle Assessment, vol. 17, pp. 997-1014, 2012.

Helms, H., Kamper, C., & Lambrecht, U., Carbon dioxide and consumption reduction through electric vehicles. *Advances in Battery Technologies for Electric Vehicles*, pp. 17-34, 2015.

Kucukvar, M., Alawi, K. A., Abdella, G. M., Bulak, M. E., Onat, N. C., Bulu, M., and Yalçıntaş, M., A frontier-based managerial approach for relative sustainability performance assessment of the world's airports, *Sustainable Development*, 2020.

Kucukvar, M., Haider, M. A., and Onat, N. C., Exploring the material footprints of national electricity production scenarios until 2050: the case for Turkey and UK, *Resources Conservation and Recycling*, vol. 125, pp. 251-263, 2017.

© IEOM Society International

Kutty, A. A., Yetiskin, Z., Abraham, M. M., Nooh, M. A., Kucukvar, M., and Abdalla, G. M., An Empirical Assessment on the Transportation Sustainability Indicators and their Impact on Economic Productivity, *Proceedings of the 5th NA Conference on Industrial Engineering and Operations Management*, Detroit, Michigan, USA, August 10-14, 2020.

Kutty, A. A., Abdella, G. M., and Kucukvar, M., Ridge Penalization-based weighting approach for Eco-Efficiency assessment: The case in the food industry in the United States. *In IOP Conference Series: Materials Science and Engineering*, vol. 947, no. 1, pp. 012003, IOP Publishing, 2020a.

Kutty, A. A., Abdella, G. M., Kucukvar, M., Onat, N. C., and Bulu, M., A system thinking approach for harmonizing smart and sustainable city initiatives with United Nations sustainable development goals. *Sustainable Development*, vol. 28, pp. 1347-1365, 2020b.

Kutty, A. A., and Abdella, G. M., Tools and Techniques for Food Security and Sustainability Related Assessments: A focus on the Data and Food Waste Management System, *Proceedings of the 5th NA Conference on Industrial Engineering and Operations Management*, Detroit, Michigan, USA, August 10-14, 2020.

Mascarenhas, A., Nunes, L. M., & Ramos, T. B., Selection of Sustainability Indicators for Planning: Combining Stakeholders' Participation and Data Reduction Techniques. *Journal of Cleaner Production*, vol. 92, pp. 295-307, 2015.

Nordelöf, A., Messagie, M., Tillman, A.-M., Söderman, M. L., & Mierlo , J. V., Environmental impacts of hybrid, plug-in hybrid, and battery electric vehicles—what can we learn from life cycle assessment? *The International Journal of Life Cycle Assessment*, vol. 19, pp. 1866–1890, 2014.

Onat, N. C., Abdella, G. M., Kucukvar, M., Kutty, A. A., Al-Nuaimi, M., Kumbaroğlu, G., & Bulu, M., How eco-efficient are electric vehicles across Europe? A regionalized life cycle assessment-based eco-efficiency analysis. *Sustainable Development*, sd.2186, 2021.

Onat, N. C., Kucukvar, M., & Tatari, O., Well-to-wheel water footprints of conventional versus electric vehicles in the United States: A state-based comparative analysis. *Journal of Cleaner Production*, vol. 204, pp. 788-802, 2018.

Park, Y. S., Egilmez, G., and Kucukvar, M., A novel life cycle-based principal component analysis framework for eco-efficiency analysis: case of the United States manufacturing and transportation nexus, *Journal of Cleaner Production*, vol. 92, pp. 327-342, 2015.

Yang, K., Abdella, G., and Alaeddini, A., Effect of location of explanatory variable on monitoring polynomial quality profiles. *International Journal of Engineering*, vol. 25, no. 2, pp. 131-140, 2012.

Biographies

Adeeb A. Kutty is an accomplished professional with a bachelor's degree from the University of Calicut, India, in Electrical and Electronics Engineering and a master's degree holder in Technology and Engineering Management, Universitat Rovira i Virgili, Tarragona, Kingdom of Spain. He is currently doing his Ph.D. in Engineering Management and works as a Sustainability Research Engineer in the Department of Industrial Engineering at Qatar University. His research interest area includes sustainability and systems engineering, smart cities and regional development, transportation, decision support systems, and urban dynamics.

Rania Al-Jondoub holds a bachelor's degree in Electronics and Telecommunication Engineering and is currently pursuing her master's degree in Engineering Management from Qatar University, Doha-Qatar. Her research interest includes sustainability, automation, control systems design, and project management.

Dr. Galal M. Abdella serves as the Assistant Professor in the Department of Industrial Engineering, College of Engineering, Qatar University. He is currently the graduate program coordinator for Engineering Management Program at Qatar University. His research area has always been centered on utilizing mathematics and advanced statistical data analysis for high dimensional data processing, circular economy and food security, modeling and simulating rare events, quality data modeling and analysis, and project resource management.

Prof.Tarek El Mekkawy obtained his Ph.D. in Industrial Engineering from the University of Windsor, Ontario, Canada, in 2001 and served as a Professor at Qatar University. Before joining Qatar University, he was the Professor and Coordinator of the M.Eng. Aerospace School at the Department of Mechanical and Manufacturing Engineering, University of Manitoba. He has over 100 publications, 50 of which are published in International Journals. His research areas include; operation of hybrid renewable energy systems, optimization of logistics and transportation, production planning, scheduling, and control.