Eco-efficiency of Electric Vehicles in the United States: A Life-Cycle Assessment based Principal Component Analysis

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This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science in Industrial and Systems Engineering.

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Date: 26 December 2016

Eco-efficiency of Electric Vehicles in the United States: A Life-Cycle Assessment based Principal Component Analysis

Shiva Afshar

Abstract

This research presents an integrated sustainability assessment framework for alternative electric vehicle technologies in the United States. Two methods such as life cycle assessment (LCA) and principal component analysis (PCA) are jointly used for eco-efficiency analysis of battery electric vehicles. Three scenarios are analyzed such as marginal electricity mix, average electricity mix and 100% solar energy. Three environmental (water withdrawal, energy consumption and carbon emission) and one economic (life cycle cost) indicators are combined to obtain the eco-efficiency values for 49 U.S. states. First, the scenarios are compared by applying the ANOVA and Tukey HSD test approaches regarding their environmental and economic indicators values. Then, a comparison is executed based on the eco-efficiency values of states in each scenario separately. The maximum scores of eco-efficiency are related to Idaho, Texas and New Mexico based on marginal electricity mix scenario, average electricity mix scenario and solar energy scenario, respectively. According to the results, solar energy scenario is the cleanest scenario because of the least value of environmental impacts while the marginal electricity mix scenario has the highest economic output. Compared to other two scenarios, solar energy scenario cause an extreme decrease in the amount of carbon emission in all states and also reduces the value of water consumption and energy use considerably in most of the states.

Keywords:

Life cycle assessment, principal component analysis, eco-efficiency, electric vehicles, sustainable transportation, policy analysis.

Amerika Birleşik Devletleri'ndeki Elektrikli Araçların Eko-Verimliliği: Yaşam döngüşü Analizi bazlı Temel Bileşenler Analizi

Shiva Afshar

Öz

Bu araştırma Amerika Birleşik Devletleri'ndeki alternatif elektrikli araç teknolojileri için entegre edilmiş sürdürülebilirlik değerlendirme çerçevesi sunmaktadır. Yaşam döngüsü değerlendirmesi (LCA) ve temel bilesenler analizi (PCA) metodları elektrikli bataryalı araçların eko-yeterlilik analizinde birlikte kullanılmıştır. Marjinal elektrik kullanımı, ortalama elektrik kullanımı ve solar enerji ile şarj edilenler dikkate alınarak üç senaryo incelenmiştir. Üç çevresel (su çekilmesi, enerji tüketimi ve karbon emisyonu) ve bir ekonomik (yaşam süresi maliyeti) gösterge birleştirilerek ABD'nin 49 eyaletinin eko-yeterlilik değerleri elde edilmiştir. İlk olarak, her bir eyaletin eko-yeterlilik değerleri her bir senaryoda ayrı bir şekilde karşılaştırmalı olarak uygulanmıştır. Eko-yeterliliğin maksimum değerleri Idaho, Texas ve New Mexico sırasıyla marjinal elektrik kullanımı senaryosu, ortalama elektrik kullanımı senaryosu ve solar enerjisi senaryosu ile ilişkilendirilmiştir. Daha sonra bu senaryolar ANOVA ve Tukey HSD test yaklaşımlarıyla çevresel ve ekonomik gösterge değeleri uygulanarak karşılaştırılmıştır. Sonuçlara göre, solar enerji senaryosu en az çevresel etki değeri ile en temiz senaryo olurken marjinal elektrik kullanımı senaryosu en yüksek ekonomik maliyet elde etmiştir. Diğer iki senaryoyla kıyaslandığında, solar enerji senaryosu bütün eyaletlerde karbon emisyonu miktarını en üst düzeyde azaltırken birçok eyalette ise su çekilmesi değerini ve enerji tüketimini önemli oranda düşürmüştür.

Anahtar Sözcükler: yaşam süresi değerlendirmesi, temel bilesenler analizi, eko-yeterliliğin, elektrikli araç teknolojileri, sürdürülebilir ulaşım, politika uygulamaları.

Dedicated To My Family.

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Abbreviations

LCA	**L**ife **C**ycle **A**ssessment
LCC	**L**ife **C**ycle **C**ost
PCA	**P**rinciple **C**omponent **A**nalysis
DEA	**D**ata **E**nvelopment **A**nalysis
CEI	**C**omposite **E**nvironmental **I**mpacts
BEV	**B**attery **E**lectric **V**ehicle
EV	**E**lectric **V**ehicle
EE	**E**co **E**fficiency
ANOVA	**AN**alysis **O**f **VA**riance
HSD	**H**onest **S**ignificant **D**ifference
AL	**A**lbama
AZ	**A**rizona
AR	**A**rkansas
CA	**C**alifornia
CO	**C**olorado
CT	**C**onnecticut
DE	**D**elware
DC	**D**istrict of **C**olumbia
FL	**F**lorida
GO	**G**eorgia
IA	**I**owa
ID	**I**daho
IL	**I**llinois
IN	**I**ndiana
KS	**K**ansas

KY	Kentucky
LA	Louisiana
MA	Massachusetts
ME	Maine
MD	Maryland
MI	Michigan
MN	Minessota
MS	Mississippi
MO	Missouri
MT	Montana
NE	Nebraska
NH	New Hampshier
NM	New Mexico
NV	Nevada
NJ	New Jersey
NY	New York
NC	North Calorina
ND	North Dokata
OH	Ohio
OK	Oklahoma
OR	Oregon
PA	Pennsylvania
RI	Rhode Island
SC	South Carolina
SD	South Dakota
TX	Texas
TN	Tennessee
UT	Utah
VT	Vermont
VA	Virginia
WA	Washington
WV	West Virginia
WI	Wisconsin

WY	**W**yoming

Chapter 1

Introduction

1.1 The U.S. transportation impacts in terms of economy and environment

Environmental issues like global warming, water pollution, air quality, and high rates of natural resources consumption have become major global concerns during recent decades. An increasing rate of fuel consumption in industrial sectors and transportation networks is considered to be an influential cause of these environmental concerns. These concerns are even more highlighted in progressive countries like the U.S. because of the huge and growing transportation and industrial sectors. The transportation sector in the U.S. consumes almost 30% of the total energy used in the whole country, and about 92% of this amount is supplied by petroleum products [2]. The amount of oil required to satisfy the transportation demand is 70% of the entire oil consumption in the U.S., and about 65% of this amount is used by personal vehicles [3]. This great amount of fuel consumption makes the transportation sector the second largest emitter of GHG after the electricity sector [4]. Hence, in recent decades alternative vehicles like electric vehicles (EVs) have been considered as appropriate solutions for environmental problems. For example, their lower tailpipe emissions and energy consumption compared to internal combustion vehicles (ICVs) make them more sustainable options [5].

1.2 Life cycle assessment models and applications in transportation

In order to quantify the environmental impacts of EVs, the life cycle assessment technique (LCA) is widely used in the literature. The LCA technique is popular because of assessing environmental impacts of producing a product or transportation activities from cradle to gate including raw material extraction, production, distribution, consumption and end of life [6].

Three main LCA approaches has been vastly used to measure the environmental impacts of a system: process-based LCA, input output based LCA and hybrid LCA [7]. In a process- based approach all the inputs and outputs are considered for each step of life cycle. The total output of the system is obtained as the summation of the output of each step. For the systems which have numerous inputs and outputs, process-based method becomes so complicated [8]. Economic input -output LCA can deal with this problem because of computing environmental impacts by considering the transactions between the different life cycle steps. On the other word, the process-based LCA includes almost all the detailed transactions in each step, where in input output LCA the transactions among the sectors are clearly determined. The hybrid LCA is an approach which aims to overcome the disadvantages of two previous methods. This method applies process-based and input output LCA in parallel [8].

In many studies, LCA has been applied to assess sustainability. [9] assessed environmental impacts of conventional vehicles, HEVs, BEVs and PHEVs in the U.S. for the entirety of their life cycle time regarding 19 indicators based on two different charging systems. [10] utilized input output LCA to measure greenhouse gas emissions of plug-in hybrid electric vehicles. [11] used an EIO-LCA to compare the sustainability of three types of electric vehicles for the 50 states of the U.S based on the driving patterns, battery structures and energy preparation scenarios. [12] used LCA approach to compare EVs and Internal combustion vehicles based on their economic and environmental impacts. [13] used EIO-LCA to measure the economic, environmental and social impacts of some U.S construction sectors. [14] compared the environmental sustainability index of hydrogen versus electric vehicles by utilizing the LCA techniqe in Tuscany,Italy. [15] used LCA to make a comparision between the present mid-sized passenger vehicles and those of the future based on their fuel consumption types. [16] utilized jointly IO-LCA and multicriteria optimization technique to determine the most sustainable passenger vehicle type for each states of U.S. [17] made a comparison between the sustainability performance of plug-in and wireless charging electric bus systems regarding energy and greenhouse gas indicators by using a process-based LCA approach.

1.3 Sustainability performance assessment indicators and Eco efficiency

There are several indexes being used to assess the sustainability performance in a system. Social, environmental and economic indexes are widely applied in the literature of transportation sustainability [18, 19]. In order to assess each index the indicator selection step is required. The indicators essentially should be clear, precise and reliable enough to result in unbiased assessments [20]. Several environmental indicators like, water consumption, energy use, CO2 emission are accounted for quantifying the environmental sustainability index (ESI) in a system. Economic indicators such as tax, profit and investment and social indicators like employment, income, human health, and welfare are used to assess the economic sustainability index and social sustainability index, respectively.

Eco-efficiency is one of the metrics vastly applied in many studies for assessing the sustainability performance. [21–23]. This is mostly because it can consider both economic and environmental sustainability indexes in the computations [24].

In spite of being a popular and efficient approach, computing Eco- efficiency becomes complicated in case of having many environmental indicators with different measuring units. In order to reduce the complexity of computations of these cases, some weighting models are utilized to reduce the dimension of variables. However, the results obtained from these models are influenced by the weight values. Some linear programming techniques including data envelopment analysis (DEA) and principle component analysis (PCA) are more suitable alternatives because of their independency to the subjective weights [22]. DEA approach is applicable to measure the environmental impact of a system for multi-attributed data and also have the capability to deal with spurious, modal and outlier data [25]. However, the results obtained from this approach are not reliable when the correlation exists between the indicators. If the indicators are correlated to each other, PCA approach is a suitable alternative duo to dealing with correlated indicators and it obtains rigorous results [22].

1.4 The novelty and organization of the research

In this study, data of three different scenarios are used from [11].1) State- based average electricity generation mix scenario considers the average electricity generation in the U.S., 2) the state- based marginal electricity mix generation scenario is based on the marginal electricity generation in the U.S. and 3) 100% solar power charging stations scenario just utilize solar energy as the resource of energy for battery charging system. Based on these three scenarios the sustainability performances of battery electric vehicles (BEVs) are evaluated across the U.S. in the operational phase of their life cycle. Eco-efficiency is used as one of the well-known metrics to assess the sustainability which provide a quantifiable combination of economic benefits and environmental impacts. To assess the environmental impacts regarding three environmental indicators (carbon footprint, energy use and water consumption) a two-phased model of LCA and PCA is developed.

Additionally, the states are ranked based on their eco-efficiency values for each scenario. Furthermore, a judgment is done to determine the best charging scenario based on their environmental and economic consequences. In the rest of the study the literature review is explained in chapter 2, methodology and data description is explained in chapter 3. The results of LCA, eco-efficiency and ANOVA and Tukey HSD test are presented in chapter 4. Finally,chapter5 consists of the conclusion, limitation of the work and potential future work.

Chapter 2

Literature Review

2.1 Studies of sustainability performance benchmarking such as DEA and PCA

PCA is widely used in the literature of sustainability since in most of the studies there are numerous indicators and dimension reduction techniques are required. Soler Rovira and Soler Rovira [26] used PCA to compute composite sustainability index for fresh apple trade in 36 countries. Salvati and Carlucci [27] used a PCA approach in a case study of Italy to determine the contribution between 99 indicators and also determining their contribution in sustainability index obtained by factor weighting model. Reisi et al. [28] obtained a sustainability index for transportation in Melbourne using a PCA approach to combine 9 social, environmental and economic indicators. Bolcarova and Kolosta [29] ranked 27 countries in Europe by considering their aggregated sustainability development index regarding environmental, social and economic indicators by using PCA approach. Mascarenhas et al. [30] used PCA to reduce the number of indicators used to compute the sustainability score of the Algrave's spatial plan. Mainali and Silveira [31] applied a PCA approach to find a composite sustainability index to assess the performance of ten energy systems for rural electrification industry in India. Ghaemi et al. [32] computed a sustainability index to evaluate the soil quality in Astan-Qods in Iran by using PCA for 9 soil-environmental indicators. Dong et al. [33] applied PCA approach to compute the sustainability index of natural gas industry in China.

DEA is another approach to obtain composite sustainability index. This technique is widely used in the literature of economic-production [34]. For example, Sueyoshi and Wang [35] used a DEA approach for an environmental assessment in U.S. energy industry to propose to improve both economic and environmental aspect of their service. Tajbakhsh and Hassini [36] evaluated supply chin networks which try to maximize the economic benefits and minimize the environmental effects by developing a multi-stage DEA model to assess the sustainability indexes of a manufacturing sector and a bank sector. Faramarzi et al. [37] proposed a new Network DEA model to assess the efficiency in a combined cycle power plant regarding social, environmental and economic indicators. Liu et al. [38] computed three indicators as environmental efficiency, economic efficiency and unified efficiency using DEA approach to evaluate the sustainability of consolidation policy in China's coal mining industry. Balezentis et al. [39] measured the environmental performance index by applying DEA approach for Lithuanian economic sectors. Schoenherr and Talluri [40] used a comparative analysis to compare the environmental sustainability initiative which is calculated by DEA approach for some plants in U.S. and Europe to survey its relation with the plants efficiency scores. Egilmez and Park [41] computed energy and carbon footprint using EIO-LCA and then computing the Eco-efficiency of U.S. manufacturing sectors by applying DEA approach. Tianqun and Yuepeng [42] computed the eco-efficiency for a real data set including eleven years data of Wuhan by using DEA approach. Lahouel [43] applied DEA approach for seventeen firms in France to measure eco-efficiency.

Chapter 3

Methodology

3.1 LCA and PCA approach

Three environmental and one economic indicators are considered to obtain the eco-efficiency as the ratio of economic output to environmental index. In order to obtain a specific value for environmental impact index LCA and PCA approaches are jointly used. The life cycle impacts corresponding to the environmental and economic indicators computed by applying LCA is the input of PCA to make a specific value as the composite environmental impacts (CEI) [22]. The application of PCA method is explained in section 3.3 in detail. In order to prevent having negative values of CEI a large enough positive number should be added to the output of PCA. To calculate the eco-efficiency, both direct and indirect economic output are considered. Life cycle cost (LCC) as an influential factor in the GDP of a country is used as economic output. The LCC is the nominator and the CEI is the denominator of the eco-efficiency ratio. The states with higher eco-efficiency scores may have either higher economic benefits or less environmental impacts or both of them. Figure.3.1 shows the steps to construct the eco-efficiency.

3.2 Life cycle assessment of Battery electric vehicles

The operation phase is the most energy-water-carbon intensive phase as well as spatially more sensitive compared to manufacturing and end-of-life phases. Therefore, the

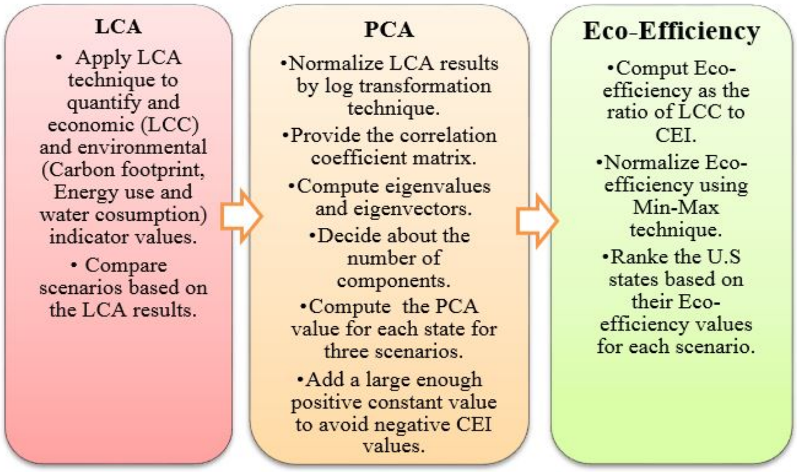

FIGURE 3.1: The steps to calculate Eco-efficiency.

manufacturing and end-of-life impacts are not considered. The functional unit of the LCA is per vehicle-miles traveled (VMT). The operation phase impacts are composed of well-to-tank (WTT) and tank-to-wheel (TTW), which are upstream and direct impacts, respectively. Since there is no direct water consumption and tailpipe emissions in the operation phase of BEVs, TTW carbon emissions and water consumptions are zero for BEVs, regardless of the spatial variations. However, there are energy consumption in both WTT (the amount of energy required to generate electricity) and TTW (the amount of energy consumed during travel of a BEV) phases. Hence, the environmental impacts of BEVs can be calculated as follows:

$$F_{c,i} = FC(WTT_{c,i} + TTW_{c,i}) \tag{3.1}$$

Where, F is the footprint for the impact category c in state i. FC is per mile fuel consumption in kWh. WTT and TTW stand for well-to-tank and tank-to-wheel phase impacts in impact category c in state i. WTT impacts are calculated based on state-specific energy mixes. TTW energy consumption is equal to direct energy consumption per mile travel of an average BEV, which is approximately 0.3 kWh. Similarly, life cycle cost impacts are obtained from literature [44] for the same vehicle type and same assumptions. For more detail information about how the LCA impacts are calculated, the complete life cycle inventory, and data source, please see [11] and [44].

3.3 Application of PCA method

To compose the environmental sustainability index, one of the linear programming techniques is utilized to make a combination of three environmental impacts. PCA is one of the approaches using for unsupervised (data without any response variable) multi-attribute and highly correlated data. PCA is based on a linear programming approach which is widely used for reducing the dimension of multi-attribute data. This approach makes one or several components (principle components) as new variables (Z_i) which are the linear combination of the main indicators, while there are not any correlation between the components. Among all the components only a few first components include the most information and variance from dataset. Therefore, they are kept as new variables and the remains are removed from the calculations [45]. The mathematical framework of PCA is shown in Equation 3.2.

$$
\begin{aligned}
Z_1 &= a_1^t = a_{11}x_1 + a_{12}x_2 + \dots a_{1n}x_n \\
Z_2 &= a_2^t = a_{21}x_1 + a_{22}x_2 + \dots a_{2n}x_n \\
&\vdots \\
Z_p &= a_p^t = a_{p1}x_1 + a_{p2}x_2 + \dots a_{pn}x_n
\end{aligned}
\tag{3.2}
$$

Where $Z_1, Z_2, \dots, Z_p$ are the components and the a_{ij} is the coefficient of x_j in i^{th} component. Each individual component is computed as a linear combination of the variables to cover the most of the information in the dataset with the largest variance and also each component is orthogonal to its previous components.

3.3.1 *Normalizing data*

The output obtained from LCA technique is a matrix consists of the states of U.S. as the rows and three environmental indicators and economic output as the columns. This matrix is used as the base of the following calculations. Since the data obtained from the LCA has different measuring units a normalization technique is used to reduce the lopsidedness and the magnitude of environmental and economic output variables by executing a log transformation technique. This normalization will lead to have more accurate results of PCA.

3.3.2 *Finding indicators correlation matrix*

After normalizing data, correlation matrix of three environmental indicators is computed in Equation 3.3. The indicators with correlation values close to 1 (or -1) have a strong correlation.

$$r_{ij} = \frac{1}{n-1}\sum_{s=1}^{n} X_{si}X_{sj} \tag{3.3}$$

Wherer_{ij} is the correlation coefficient among indicator i and indicator j and X_{si} is the value of indicator i in state s and X_{sj} is the value of indicator j in state s.

3.3.3 *Computing eigenvalues and eigenvectors*

In order to decide about the number of components in the PCA, eigenvalues in Equation 3.4.

$$|R - \lambda I| = 0 \tag{3.4}$$

Where R is the indicators correlation matrix and λ represents the eigenvalues and I is the unit matrix. The eigenvalues obtained from Equation 3.4 are attributed to each principle component. The largest eigenvalue is attributed to the first principal component since it should have the maximum percentage of variance. the percentage of variance corresponding to component j is calculated by Equation 3.5.

$$\text{percentage of variance} = \frac{\lambda_j}{\sum_{j=1}^{n}\lambda_j} \tag{3.5}$$

In order to compute the principal component values Eigenvectors are calculated by Equation 3.6.

$$(R - \lambda_j I)F_j = 0 \tag{3.6}$$

Where λ_j is the eigenvalue of component j and F_j is its eigenvector. The coefficient of X_{ij}s in each principle component are obtained by dividing its related eigenvector over the square root of its eigenvalue [26].

3.3.4 *Deciding about the number of components*

The components which their eigenvalues are grater or equal to 1 and consequently include high variance in dataset are used to calculate PCA values and the remains are omitted, since they do not include a large amount of variability of dataset and do not have any impressive effects in our results. If only the eigenvalue of the first principle component is equal or greater than one it is principle component; otherwise, PCA value is a linear combination of those Z_j s which their eigenvalues are greater or equal to 1 (Equation 3.7) [33].

3.3.5 *Computing the PCA values for each state for three different scenarios*

After computing principal components we can compute PCA value using Equation 3.7 for each state for 3 different scenarios.

$$\text{PCA value} = \frac{\lambda_1 Z_1 + \lambda_2 Z_2 + \ldots + \lambda_j Z_j}{\lambda_1 + \lambda_2 + \ldots + \lambda_j} \tag{3.7}$$

3.3.6 *Adding a large enough positive value to PCA values to avoid non-positive values*

We added a large enough number to each PCA value(See Equation 3.8) to avoid non-positive amounts as our CEI [46].

$$CEI_i = PC_i + \epsilon \tag{3.8}$$

Where CEI_{ij} the composite environmental impact score of is state i, PC_i is the PCA score of state i and ϵ is a positive constant number and is bigger than the smallest negative PCA score.

3.4 Mathematical framework for Eco-efficiency

For calculating the eco-efficiency as an index of the performance of electric vehicles regarding both environmental and economic aspects, the raw eco-efficiency is defined as a ratio of life cycle cost (LCC) to composite environmental impacts (CEI))(Equation 3.9).

$$Eco-efficiency = \frac{LCC}{CEI} \tag{3.9}$$

In order to make the eco-efficiency score comparable between the states , the raw eco-efficiency values are rescaled by applying a min-max technique(Equation 3.10) which is used by [22] as well.

$$Normalized(E_i) = \frac{E_i - E_{min}}{E_{max} - E_{min}} \tag{3.10}$$

E_i is the raw eco-efficiency value for state i and E_{min} and E_{max} are the minimum and maximum values of eco-efficiency among all the states, respectively.

Chapter 4

Results

4.1 LCA Results

The LCI results for the environmental indicators which are computed by applying EIO-LCA approach for three scenarios are shown in Figure 4.1, 4.2, 4.3.

In scenario 1, according to Figure. 4.1, WV is the state with maximum amount of carbon emission. IN and KY are the second and third states with the highest amount of carbon footprint, respectively. VT is the first and ID is the second state with minimum amount of carbon footprint. The observations in Figure 4.2 show that the energy consumption has the same pattern as carbon footprint. IN, OH, WV and KY are the states with high amount of energy consumption while ID consumes the least amount of energy. Figure 4.3 presents that, ID, WA, OR and VT which are among the states with low amount of energy and carbon footprint, consume the highest amount of water. As a result, the amount of energy use has a direct relation with carbon footprint while it is obvious that the amount of Water use has the inverse relation with other 2 indicators.

In scenario 2, Figure 4.4, 4.5, 4.6 shows that, IL has the highest level of water use, Energy consumption and carbon emission. OH, MI, IN, KY and WV have almost the second largest amount of water use and carbon emissions. In Figure 4.5, the amount of energy consumption has its largest amount in IL also some north eastern states (MA, RI, CT, VT, ME and NH) have the large amount of energy consumption. TX has the minimum amount of carbon footprint and water use and a low amount of energy consumption among all the states. Since there are strong and positive relations between

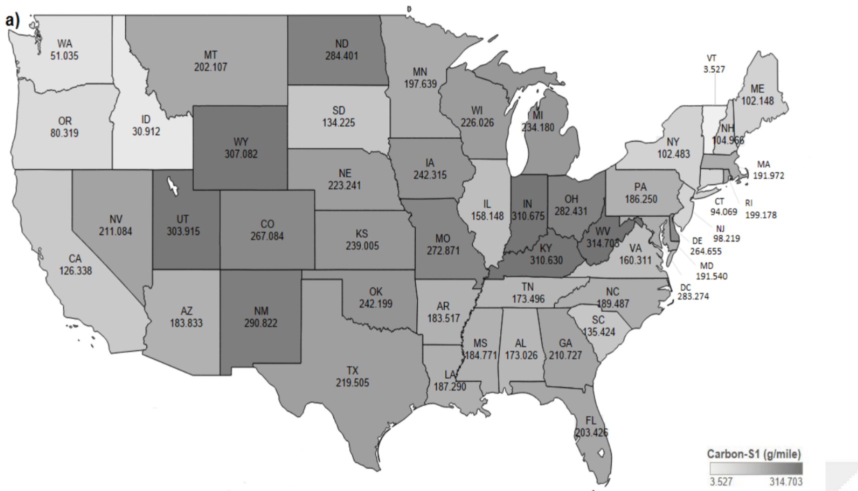

FIGURE 4.1: LCA results of Carbon footprint (g/mile) in scenario 1.

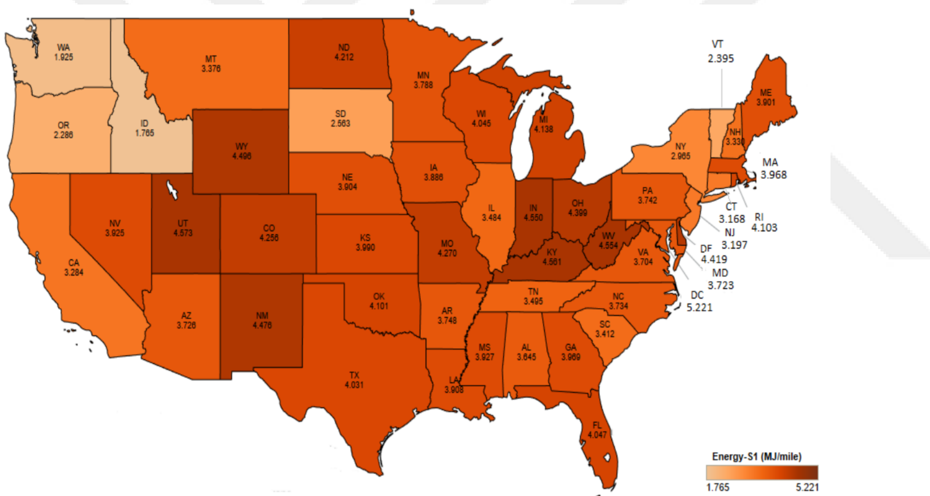

FIGURE 4.2: LCA results of energy footprint (MJ/mile) in scenario 1.

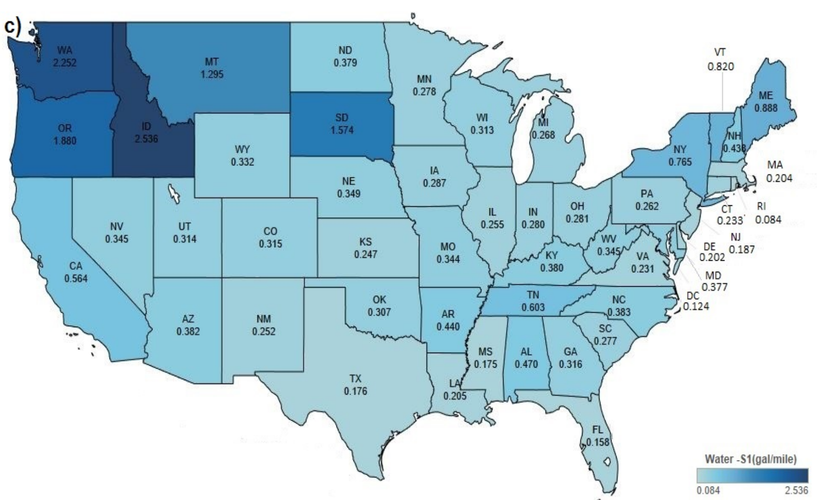

FIGURE 4.3: LCA results of water footprint (gal/mile) in scenario 1.

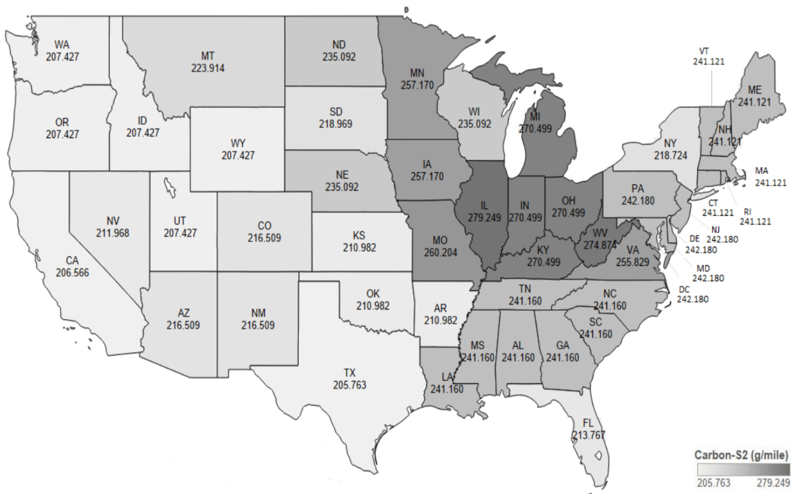

FIGURE 4.4: LCA results of carbon footprint(g/mile) in scenario 2.

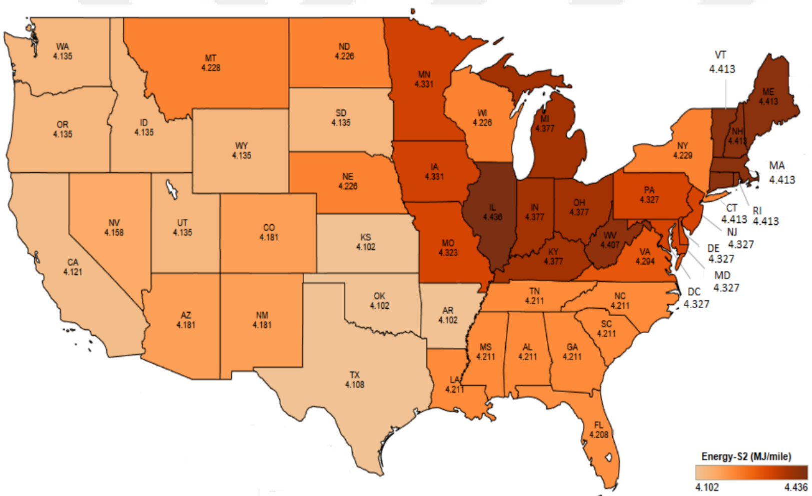

FIGURE 4.5: LCA results of energy footprint (MJ/mile) in scenario 2.

three indicators in this scenario, we can observe that the states with high (low) amount of one indicator also have high (low) amounts for other 2 indicators.

In scenario 3, the policy is using only solar energy to charge the batteries. Therefore, as it is shown in Figure 4.7, 4.8 and 4.9,the emission of carbon has been decreased considerably in comparison with other two scenarios. The level of energy consumption (See Figure 4.8) and water use (See Figure 4.9) also has the remarkable reduction compared to scenario 1 and scenario 2. In this scenario, IL has the maximum value of energy consumption, water use and carbon emissions and consequently maximum environmental impact. After IL, PA and NY are second and third states which have the highest amount of energy

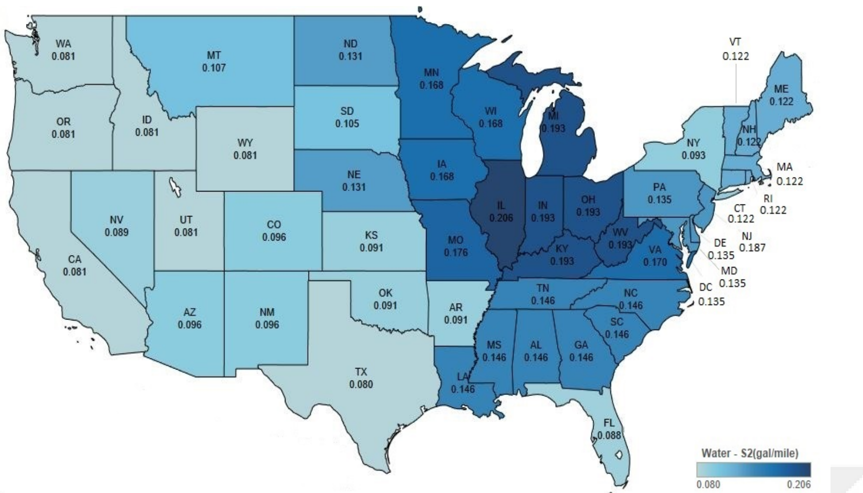

FIGURE 4.6: LCA results of water footprint (gal/mile) in scenario 2.

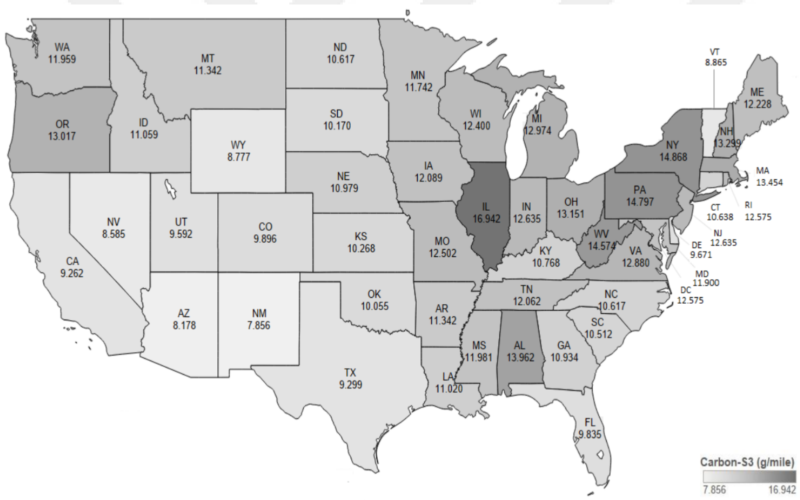

FIGURE 4.7: LCA results of Carbon footprint (g/mile) in scenario 3.

consumption, water use and carbon emissions. NM is the state that has the minimum amount of effect on the environment duo to its low amount of environmental indicators.

By utilizing the LCA and economic output values of the states for each scenario, a comparison between three scenarios is made by applying the Analysis of Variance (ANOVA) technique. ANOVA (analysis of variance) is a statistical technique widely utilized to compare the means of several populations in previous studies [47, 48]. This comparison is essentially a statistical hypothesis testing in which the null hypothesis (H_0) is that all population means are equal with confidence of $1 - \alpha$. ANOVA considers the proportion of variance between the populations over the variance within the populations and calculates an F-value. For the large amount of F-value, it will be more likely to reject

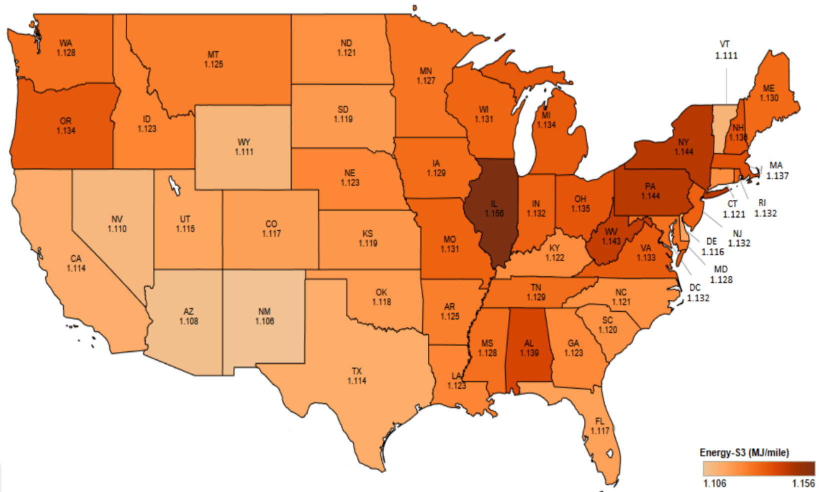

FIGURE 4.8: LCA results of energy footprint(MJ/mile) in scenario 3.

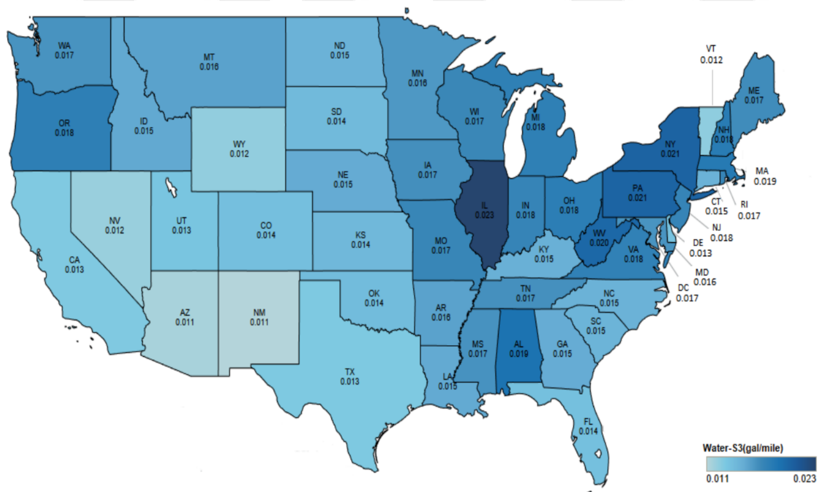

FIGURE 4.9: LCA results of Water footprint (gal/mile) in scenario 3.

the null hypothesis. If the corresponding P-value of F-value which is extracted from F distribution is less than the α , the null hypothesis is rejected and claim that the means of the populations are not equal. The framework of ANOVA is shown in Equation 4.1 [49].

$$
\begin{aligned}
&H_0 : M_1 = M_2 = M_3 \\
&H_1 : \text{At least two scenarios have different averages for one specific indicator.}
\end{aligned}
\tag{4.1}
$$

Where, M_1, M_2 and M_3 are the average of each environmental indicators in scenario 1, 2 and 3, respectively. In this study , In order to determine the difference between the means of each indicator in three scenarios the one way- ANOVA technique is used with 95% confidence interval. The results of ANOVA are provided in Table 4.1. The results demonstrate that, for all four variables (carbon, water, energy and LCC) the null hypothesis is rejected due to its very small P-values (0.000 $<$ 0.05) . These results (See Table 4.1) shows that the alternative hypothesis (H_1) will be true and at least two scenarios do not have equal means for each indicator.

Table 4.1: ANOVA results

		DF	**Sum. Squ**	**Mean.Squ**	**F-Value**	**P-Value**
Carbon	Between Groups	2	1397359	698679	330	0
	Whitin Groups	144	304889	2117		
Water	Between Groups	2	6.21	3.11	33.45	0
	Whithin Groups	144	13.37	0.09		
Energy	Between Groups	2	277.6	138.8	843.2	0
	Whithin Groups	144	23.7	0.16		
LCC	Between Groups	2	3	1.5	30.4	0
	Whithin Groups	144	7.1	0.05		

Considering the results that are obtained from ANOVA (null hypothesis is rejected for all four indicators) at least there are two scenarios for each indicators that have unequal averages. Therefore, to determine which scenarios have different means for each indicator, one method is doing t-tests for each two scenarios but this method will increase the type I error (The probability of rejecting a true null hypothesis). There is another method which is used very common after observing the rejection of H_0 in ANOVA which called Tukey HSD test. This test defines confidence intervals for each two groups and with regard to their difference of averages determines whether there is any significant difference between their means or not [50].

The results of Tukey test which have been shown in Table 4.2, represent that for carbon, energy and LCC the differences between each two scenarios are significant because their lower and upper bound values have the same sign (both of them are positive or negative) and zero is not in their confidence interval; on the other word, $M_i - M_j$ are not equal to zero. The small amounts of P-value (0.000 $<$ 0.05) also illustrate that the null hypothesis is rejected for each two scenarios except water consumption in scenario 2 and 3 since zero is in the interval of their lower and upper bound and consequently, the P-value (0.16) is not small enough to reject H_0. (See Table 4.2)

Regarding the results that we obtained from the ANOVA and Tukey-tests and by considering the averages of three environmental variables, the third scenario has the minimum

TABLE 4.2: Tukey HSD -test results

		Mi-Mj	Lower Bound	Upper Bound	P-value
	Scenario2- 1	40.12	18.11	62.14	0
Carbon	Scenario3- 1	-183.82	-205.83	-161.8	0
	Scenario 3-2	-223.95	-245.96	-201.93	0
	Scenario 2-1	-0.37	-0.51	-0.22	0
Water	Scenario 3-1	-0.48	-0.63	-0.34	0
	Scenario 3-2	-0.11	-0.26	0.03	0.16
Energy	Scenario 2-1	0.5	0.3	0.69	0
	Scenario 3-1	-2.64	-2.83	-2.44	0
	Scenario 3-2	-3.13	-3.33	-2.94	0
	Scenario 2-1	-0.35	-0.45	-0.24	0
LCC	Scenario 3-1	-0.21	-0.32	-0.11	0
	Scenario 3-2	0.13	0.03	0.24	0

amount of carbon and energy footprint with significant differences compared to scenario 1 and 2 and the water consumption also has the least value among three scenarios although its difference is not remarkable in comparison with scenario 2 .

Considering the descriptive statistics of three environmental indicators which are provided in Table4.3, The average of carbon emission of first and second scenarios are 16.98 and 20.47 times while the means of water consumption are 25 and 6.5 times and the averages of energy use are 3.33 and 3.77 times more than scenario 3,respectively.

Consequently, scenario 3 is the best scenario considering its extreme lowest environmental impacts in comparison with the first and second scenarios. Scenario 2 has the lower averages of carbon emission and energy consumption but the higher average of water consumption in comparison with scenario 2 (See Table 4.3). LCC is another index which has the important effect on the eco-efficiency scores. Scenario 1 had the highest average of economic output among all three scenarios. The second average of economic output is related to third scenario and scenario 1 has the minimum amount of economic output. (See Table 4.3)

4.1.1 Results of principal component analysis

The average of correlation coefficients among the indicators for three scenarios are presented in Table 4.4.There are strong positive correlations among all indicators in scenario

Table 4.3: Descriptive statistics of variables

		Range	Min	Max	Mean	Std.deviation
Scenario 1	Water	2.45	0.08	2.54	0.5	0.52
	Carbon	311.18	3.53	314.7	195.32	76.06
	Energy	3.46	1.77	5.22	3.76	0.69
	LCC	0.62	3.02	3.64	3.37	0.16
Scenario2	Water	0.13	0.08	0.21	0.13	0.04
	Carbon	73.49	205.76	279.25	235.45	20.81
	Energy	0.34	4.1	4.44	4.26	0.11
	LCC	0.46	2.84	3.3	3.02	0.12
Scenario 3	Water	0.01	0.01	0.02	0.02	0
	Carbon	9.08	7.86	16.94	11.5	1.87
	Energy	0.05	1.11	1.16	1.13	0.01
	LCC	1.6	2.4	4	3.15	0.32

1 and 2. This means that the more water and fuel are consumed, the more energy is used.

Table 4.4: The correlation coefficient (CC) among carbon (C),water (W) and energy (E) footprints in three scenarios

	Scenario 1			**Scenario 2**			**Scenario 3**		
CC	**W**	**E**	**C**	**W**	**E**	**C**	**W**	**E**	**C**
Water	1	-0.79	-0.58	1	0.69	0.97	1	0.96	0.99
Energy	-0.79	1	0.9	0.69	1	0.83	0.96	1	0.97
Carbon	-0.58	0.9	1	0.97	0.83	1	0.99	0.97	1

In all scenarios except scenario 1, all indicators have strong and positive correlations but in scenario 1 the water withdrawal indicator has a negative correlations with the amount of energy consumption and carbon footprint. Regarding to the significant correlations between the indicators we used PCA method to compute CEI index. The values of percentage of variance and eigenvalue of the PCA components are shown in Table 4.5.

Table 4.5: The eigenvelues and percentage of variance (POV) of the components in three scenarios

	Scenario 1		**Scenario 2**		**Scenario 3**	
	Eigenvalue	**POV**	**Eigenvalue**	**POV**	**Eigenvalue**	**POV**
Component 1	2.4	79.89	2.68	89.5	2.98	99.38
Component 2	0.48	15.94	0.31	10.21	0.02	0.5
Component 3	0.12	4.17	0.01	0.29	0	0.12

In order to decide about the number of component to obtain PCA values, it is necessary to select the components which their cumulative percentage of variances cover the most information in the dataset. Therefore, their eigenvalue should be greater or equal to 1.For all three scenarios only the first components have the most percentage of variance (79.9, 89.87 and 97.28) and their eigenvalues are more than 1. (See Table 4.5) Therefore, the first component (Z_1) is used to obtain PCA vales for all three scenarios.

The correlation between each indicator and the first component are shown for three scenarios in Table 4.6. In scenario 1 there are strong positive correlation between Energy consumption and Carbon emission values and the scores of PCA, while there is a strong negative correlation between the water consumption values and PCA. This means that by increasing the value of water consumption PCA value is decreasing in this scenario. For second and third scenario all the correlations are positive and close to 1. Therefore, by increasing the values of each indicator PCA value is increasing, consequently.

TABLE 4.6: The correlation between the variables and the first components

	Scenario 1	**Scenario 2**	**Scenario 3**
Energy	0.96	0.89	0.99
Carbon	0.86	0.99	0.99
Water	-0.85	0.95	0.99

The variables factor maps show the vector of the environmental indicators in three scenarios. Dim 1 and Dime 2 display the percentage of variance of the first and second component in PCA, respectively (See Figure 4.10). The negative correlations among water consumption and energy use and carbon footprint due to their opposite directions are observed in the first scenario, where all other indicators in scenario 2 and 3 have the positive correlations. In all three scenarios the first components (Dim 1) represent the largest percentages of variance. Furthermore, the correlations among the indicators and their related PCA scores are also observable by drawing an orthogonal line from the endpoint of each vector to the Dim 1 axis for each dimension. The greatest correlations among PCA values and environmental indicators belong to third scenario, since in case of the obtained value is very close to 1.

For computing the composite environmental impact (CEI), after doing log transformation to reduce the skewness of environmental indicators and economic output, PCA is applied for each scenario. A large enough number (6) is also added to each computed PCA value to avoid having the negative values as the CEI. Then, the eco-efficiency scores as a ratio of life cycle cost over composite sustainability index for three scenarios are computed

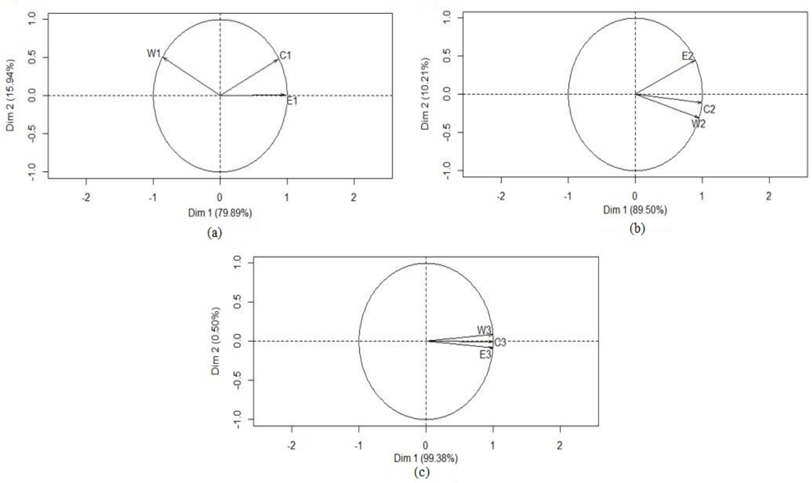

FIGURE 4.10: The variables factor map (PCA) for a) Scenario 1, b) Scenario 2 and c) Scenario 3.

for all the states. Afterward, the states are ranked considering their descending orders of eco-efficiency scores. The values of CEI and log transformed LCC and eco-efficiency scores of 49 states are shown in Table 4.7.

The values of eco-efficiency in Table 4.7, present the raw eco-efficiency values which are obtained by dividing the LCC values of different states in to the CEI values. To rescale the values of raw-eco efficiency we used the min-max technique (Equation.3.9) to normalize the raw-eco-efficiency scores and put them into the zero and one interval .The values of normalized eco-efficiency for three scenarios are shown in Figure 4.11, 4.12 and 4.13.

In scenario 1, ID has the highest amount of eco-efficiency. Since the eco-efficiency has a direct relation with life cycle cost (LCC) value and the inverse relation with CEI, this state has the minimum score of CEI among all the states .The amount of LCC (3.35 cents/ mile) makes it the best state by considering both economic and environmental impacts. VT is the second state which has the high value of eco-efficiency since it has the second lowest value of CEI. DC has the maximum amount of CEI and this leads to make it the least eco-efficient state. (See Figure 4.11)

In scenario 2, TX has the maximum amount of eco-efficiency due to its low value of CEI and also large enough amount of LCC. Totally, it is concluded that the western and central states have higher amount of eco-efficiency than eastern provinces because of their less environmental impacts and consequently their lower amounts of CEI which

Table 4.7: CEI and raw eco-efficiency (EE) scores for three scenarios

State	CEI1	EE1	State	CEI2	EE2	State	CEI3	EE3
ID	1.049	1.152	TX	3.447	0.308	NM	2.322	0.377
VT	1.158	0.969	CA	3.568	0.299	VT	3.341	0.375
WA	1.778	0.68	ID	3.671	0.291	AZ	2.579	0.339
OR	2.765	0.437	OR	3.671	0.291	WY	3.306	0.311
SD	3.629	0.351	UT	3.671	0.291	TX	3.962	0.294
MT	4.893	0.252	WA	3.671	0.291	NV	3.17	0.276
NY	4.41	0.251	WY	3.671	0.291	DE	4.214	0.276
CA	5.106	0.23	AR	3.846	0.279	UT	4.128	0.258
TN	5.477	0.228	KS	3.846	0.279	CA	3.947	0.252
ME	5.086	0.221	OK	3.846	0.279	FL	4.59	0.246
NH	5.203	0.216	NV	4.131	0.262	SD	4.822	0.235
NJ	5.702	0.211	SD	4.564	0.245	CO	4.612	0.231
IL	6.072	0.21	AZ	4.55	0.238	CT	5.336	0.229
AL	5.792	0.209	CO	4.55	0.238	ND	5.329	0.224
SC	5.828	0.209	NM	4.55	0.238	KS	4.856	0.219
CT	5.47	0.205	FL	4.429	0.236	OK	4.725	0.218
MD	6.104	0.202	NY	4.807	0.22	KY	5.436	0.214
AZ	6.065	0.201	MT	5.244	0.203	WA	6.584	0.211
NC	6.092	0.199	ND	5.975	0.187	SC	5.237	0.21
NE	6.42	0.198	NE	5.975	0.187	NC	5.329	0.206
AR	5.97	0.198	AL	6.29	0.181	NE	5.561	0.203
MN	6.418	0.196	GA	6.29	0.181	LA	5.574	0.203
VA	6.338	0.195	LA	6.29	0.178	GA	5.546	0.192
PA	6.383	0.193	MS	6.29	0.178	ID	5.587	0.191
WI	6.617	0.192	NC	6.29	0.178	MT	6.015	0.188
IA	6.623	0.19	SC	6.29	0.178	MD	6.354	0.188
NV	6.401	0.189	TN	6.29	0.178	MN	6.25	0.186
CO	6.887	0.187	WI	6.474	0.172	AR	6.015	0.183
MO	6.844	0.187	DC	6.758	0.163	OR	7.42	0.18
KS	6.806	0.186	DE	6.758	0.163	DC	6.986	0.175
ND	6.76	0.186	MD	6.758	0.163	WI	6.88	0.174
MI	6.832	0.185	NJ	6.758	0.163	NH	7.608	0.172
GA	6.501	0.18	PA	6.758	0.163	ME	6.775	0.172
OK	6.725	0.178	IA	7.63	0.156	VA	7.327	0.171
OH	7.116	0.177	CT	6.957	0.154	NJ	7.203	0.17
KY	7.056	0.177	MA	6.957	0.154	IA	6.678	0.169
LA	6.706	0.176	ME	6.957	0.154	MI	7.409	0.169
WV	7.138	0.176	NH	6.957	0.154	OH	7.513	0.167
WY	7.112	0.176	RI	6.957	0.154	MS	6.59	0.167
MS	6.834	0.175	VT	6.957	0.154	RI	6.986	0.166
IN	7.289	0.173	VA	7.43	0.151	MO	6.909	0.164
TX	7.037	0.169	MN	7.63	0.146	IN	7.203	0.161
UT	7.197	0.168	MO	7.764	0.145	TN	6.67	0.16
NM	7.274	0.166	KY	8.488	0.139	MA	7.894	0.151
MA	6.773	0.166	IN	8.488	0.138	WV	8.691	0.144
DE	7.338	0.164	MI	8.488	0.138	AL	8.137	0.139
FL	7.075	0.163	OH	8.488	0.138	PA	8.971	0.133
RI	7.595	0.148	WV	8.748	0.134	NY	8.988	0.133
DC	8.256	0.147	IL	9.132	0.131	IL	10.431	0.117

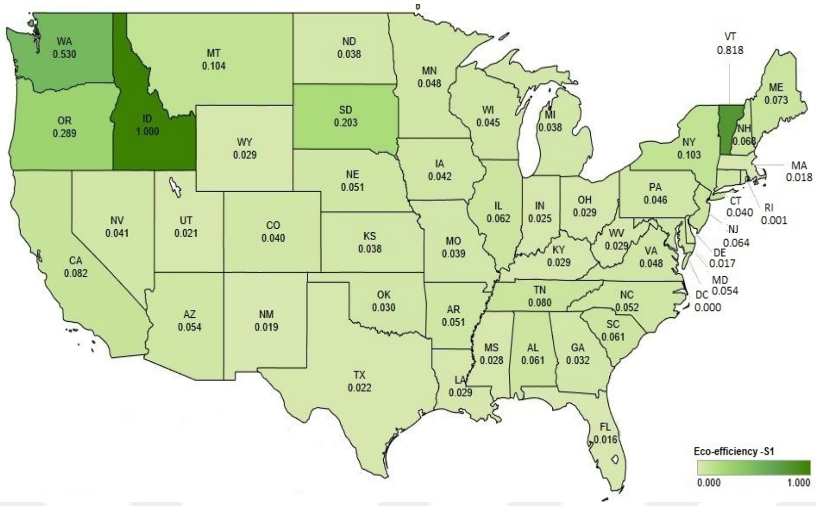

FIGURE 4.11: Eco-efficiency scores of scenario 3.

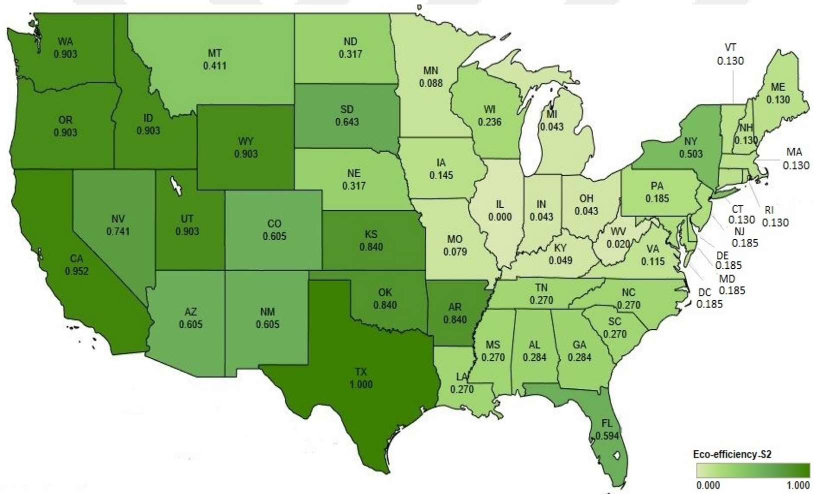

FIGURE 4.12: Eco-efficiency scores of scenario 2.

is one of the most important factors that determine the value of eco-efficiency in the states. IL has the highest values of all three environmental indicators and consequently the largest value of CEI. Although this state has the maximum amount of economic output, the large value of CEI makes it the last eco-efficient state. (See Figure 4.12)

In scenario 3, NM has the maximum amount of eco-efficiency duo to its minimum amount of CEI. VT and AZ are the second and third scenarios with high score of eco-efficiency, respectively. While the CEI value of AZ is less than VT, AZ is more eco-efficient since it has the greater value of LCC than VT. IL is the least eco- efficient has the maximum value of CEI and also its LCC score is not high enough to make a significant change in its low value of eco-efficiency. (See Figure 4.13)

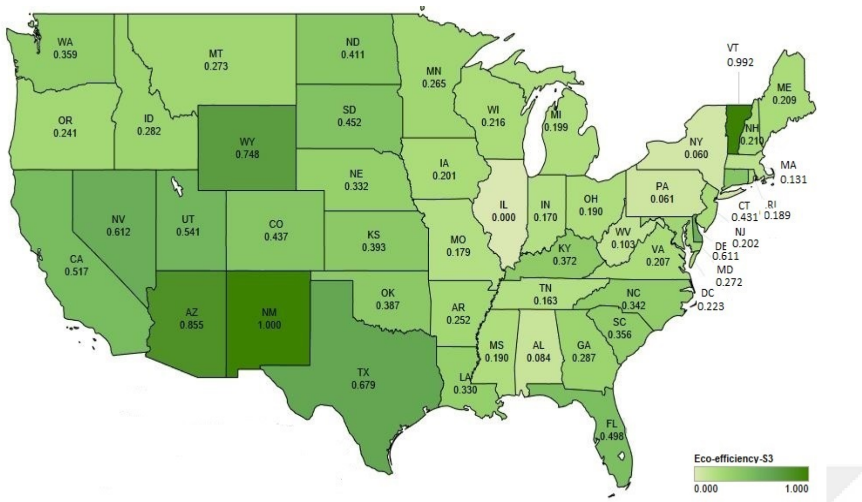

FIGURE 4.13: Eco-efficiency scores of scenario 3.

4.1.2 Comparison of eco-efficiency results with previous DEA analysis

In another study [1] the efficiency of 49 states in U.S. conducted by applying an agent-based and state benchmarking model. In, this study we survey if there is any relation between our findings and previous study. Therefore, therefore, we used a correlation analysis. The results of our survey are shown in Table 4.8.

TABLE 4.8: The correlation coefficient (CC) among this study and previous study [1]

	Scenario 1	**Scenario 2**	**Scenario 3**
CC	0.43	0.88	0.89

The high correlations, especially among scenario 2 and 3 in our study and previous study shows that there are strong and positive relationship between the results of eco-efficiency based on PCA have the strong relation with another study. (See Table 4.8)

Chapter 5

Conclusion

In this study, three environmental (CO2 emission, energy use and water consumption) and economic output indicators are considered to measure the sustainability performance of BEV s for 49 states in U.S. Three different scenarios are studied. First, the environmental impacts are quantified by applying the LCA technique. The results of comparing LCA of three scenarios by using ANOVA and Tukey-tests show that third scenario has the minimum average of all three environmental indicators and can be introduced as the cleanest scenario.

The third scenario, because of obtaining all the required energy of BEVs from the solar energy makes a reduction in the amount of carbon emission in all the states and also the value of water consumption and energy use has decreased notably in most of the states. The first scenario has the maximum value of economic output and the third and second scenarios have the second and third highest averages of economic output, respectively. Additionally, because of the high correlation between environmental indicators, the PCA approach is applied to reduce the dimension of three environmental indicators and generate a unique composite environmental impact. Next, the Eco-efficiency for each state is computed and the states were ranked regarding their increasing value of eco-efficiency. In scenario 1, ID has the highest amount of eco-efficiency. In scenario 2, TX has the maximum amount of eco-efficiency due to its lowest value of CEI. Totally we can conclude that the western and central states have higher amount of eco-efficiency than eastern provinces. In scenario 3, NM has the maximum value of eco-efficiency.

As the last step, the correlation analysis is done to determine whether there is any meaningful relation between the results obtained from previous study (DEA approach) versus this study (PCA approach).A correlation analysis among this work (PCA approach) and previous study (DEA approach) is also made. From the results it is found that there are strong positive relations between the results of two approaches in scenario 2 (0.88) and scenario 3 (0.89) and the moderate positive relations (0.43) between the results of scenario1 among two approaches.

The results of the environmental and the economic impacts of BEVs can be used for the researchers and government to make correct decisions in the transportation system. Furthermore, the method that we used in this study can be applicable for all the transportation and industries problems which are dealing with the several correlated indicators and consequently need a dimension reduction technique.

In this study the survey has been executed for just BEV s that are a small branch of passenger electric vehicles. This study can be extended by considering other types of electric vehicles like plug in-hybrid and hybrid electric vehicles. Additionally, only the operational phase of the BEVs life time is considered here. It is possible to extend it to cradle- to- gate life cycle perspective. As another limitation in this study, just the environmental impacts of BEVs are taken in to account to assess the sustainability index regardless of their economic and social impacts. In addition to Economic input output LCA model is used to assess the environmental impacts. The computations can be more accurate if using other LCA models like hybrid or process based LCA as well.

Bibliography

[1] N.C.Onat, M. Noori, M. Kucukvar, Y. Zhao, O. Tatari, and M. Chester. Exploring the suitability of electric vehicles in the united states: An integrated agent based modeling and state benchmarking approach. *Energy*, 2017.

[2] U.S. Energy Addministration. Energy use for transportation. `http://www.eia.gov/energyexplained/?page=us_energy_transportation`, 2016.

[3] American Energy Independence. American fuels. `http://www.americanenergyindependence.com/fuels.aspx`, 2016.

[4] Center For Climate and Energy Solutions. U.s. emissions. `http://www.c2es.org/energy/use/transportation`, 2016.

[5] T. R. Hawkins, B. Singh, G. Majeau Bettez, and A. H. Stromman. Comparative environmental life cycle assessment of conventional and electric vehicles. *Journal of Industrial Ecology*, 17(1):53–64, 2013.

[6] C. T. Hendrickson, L. B. Lave, and H. S. Matthews. *Environmental life cycle assessment of goods and services: an input-output approach*. Resources for the Future, 2006.

[7] L. Deng, C.W. Babbitt, and E.D. Williams. Economic-balance hybrid lca extended with uncertainty analysis: case study of a laptop computer. *Journal of Cleaner Production*, 19(11):1198–1206, 2011.

[8] G. Rebitzer, T. Ekvall, R. Frischknecht, D. Hunkeler, G. Norris, T. Rydberg, W.P. Schmidtg, S. Suhh, B.P. Weidemai, and D.W. Pennington. Life cycle assessment: Part 1: Framework, goal and scope definition, inventory analysis, and applications. *Environment international*, 30(5):701–720, 2004.

[9] N. C. Onat, M. Kucukvar, and O. Tatari. Towards life cycle sustainability assessment of alternative passenger vehicles. *Sustainability*, 6(12):9305–9342, 2014.

[10] C. Samaras and K. Meisterling. Life cycle assessment of greenhouse gas emissions from plug in hybrid vehicles: implications for policy. *Environmental science & technology*, 42(9):3170–3176, 2008.

[11] N.C. Onat, M. Kucukvar, and O. Tatari. Conventional, hybrid, plug-in hybrid or electric vehicles? state-based comparative carbon and energy footprint analysis in the united states. *Applied Energy*, 150:36–49, 2015.

[12] R. Faria1, P. Moura, J. Delgado, and A. T. de Almeida. A sustainability assessment of electric vehicles as a personal mobility system. *Energy Conversion and Management*, 61:19–30, 2012.

[13] M. Kucukvar and O. Tatari. Towards a triple bottom-line sustainability assessment of the us construction industry. *The International Journal of Life Cycle Assessment*, 18(5):958–972, 2013.

[14] I. Bartolozzi, F. Rizzi, and M. Frey. Comparison between hydrogen and electric vehicles by life cycle assessment: A case study in tuscany, italy. *Applied energy*, 101:103–111, 2013.

[15] Christian C. Bauer, J. Hofer, H.J. Althaus, A. Del Duce, and A. Simons. The environmental performance of current and future passenger vehicles: life cycle assessment based on a novel scenario analysis framework. *Applied energy*, 157:871–883, 2015.

[16] N.C. Onat, M. Kucukvar, O. Tatari, and Q.P. Zheng. Combined application of multi-criteria optimization and life-cycle sustainability assessment for optimal distribution of alternative passenger cars in us. *Journal of Cleaner Production*, 112:291–307, 2016.

[17] Z.Bi, L. Song, R. De Kleine, C.C. Mi, and G.A. Keoleian. Plug in vs. wireless charging: Life cycle energy and greenhouse gas emissions for an electric bus system. *Applied Energy*, 146:11–19, 2015.

[18] Y. Pan and H. Li. Sustainability evaluation of end-of-life vehicle recycling based on emergy analysis: a case study of an end-of-life vehicle recycling enterprise in china. *Journal of Cleaner Production*, 2016.

[19] S. Rajak, P. Parthiban, and R. Dhanalakshmi. Sustainable transportation systems performance evaluation using fuzzy logic. *Ecological Indicators*, 71:503–513, 2016.

[20] A. Sardain, Cé. Tang, and C. Potvin. Towards a dashboard of sustainability indicators for panama: A participatory approach. *Ecological Indicators*, 70:545–556, 2016.

[21] G. Egilmez, M. Kucukvar, and O. Tatari. Sustainability assessment of us manufacturing sectors: an economic input output-based frontier approach. *Journal of Cleaner Production*, 53:91–102, 2013.

[22] Y.S. Park, G. Egilmez, and M. Kucukvar. 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*, 92:327–342, 2015.

[23] O. Tatari and M. Kucukvar. Eco efficiency of construction materials: data envelopment analysis. *Journal of Construction Engineering and Management*, 138(6): 733–741, 2011.

[24] G. Huppes and M. Ishikawa. Why eco efficiency? *Journal of Industrial Ecology*, 9 (4):2–5, 2005.

[25] J. Zhu and W.D. Cook. *Modeling data irregularities and structural complexities in data envelopment analysis*. Springer Science & Business Media, 2007.

[26] J. Soler Rovira and P. Soler Rovira. Assessment of aggregated indicators of sustainability using pca: the case of apple trade in spain. 2009.

[27] L. Salvati and M. Carlucci. A composite index of sustainable development at the local scale: Italy as a case study. *Ecological Indicators*, 43:162–171, 2014.

[28] M. Reisi, L. Aye, A. Rajabifard, and T. Ngo. Transport sustainability index: Melbourne case study. *Ecological Indicators*, 43:288–296, 2014.

[29] P. Bolcárová and S. Kološta. Assessment of sustainable development in the eu 27 using aggregated sd index. *Ecological Indicators*, 48:699–705, 2015.

[30] A. Mascarenhas, L.M. Nunes, and T.B Ramos. Selection of sustainability indicators for planning: combining stakeholders' participation and data reduction techniques. *Journal of Cleaner Production*, 92:295–307, 2015.

[31] B. Mainali and S. Silveira. Using a sustainability index to assess energy technologies for rural electrification. *Renewable and Sustainable Energy Reviews*, 41:1351–1365, 2015.

[32] M.Ghaemi, A.R. Astaraei, H. Emami, M. Nassiri Mahalati, and S.H. Sanaeinejad. Determining soil indicators for soil sustainability assessment using principal component analysis of astan quds east of mashhad-iran. *Journal of soil science and plant nutrition*, 14(4):1005–1020, 2014.

[33] X. Dong, J. Guo, M. Höök, and G. Pi. Sustainability assessment of the natural gas industry in china using principal component analysis. *Sustainability*, 7(5):6102–6118, 2015.

[34] S. Athanassoglou. Revisiting worst case dea for composite indicators. *Social Indicators Research*, pages 1–14, 2015.

[35] T. Sueyoshi and D. Wang. Radial and non-radial approaches for environmental assessment by data envelopment analysis: corporate sustainability and effective investment for technology innovation. *Energy Economics*, 45:537–551, 2014.

[36] A. Tajbakhsh and E. Hassini. A data envelopment analysis approach to evaluate sustainability in supply chain networks. *Journal of Cleaner Production*, 105:74–85, 2015.

[37] G.R. Faramarzi, M. Khodakarami, A. Shabani, R.F. Saen, and F. Azad. New network data envelopment analysis approaches: an application in measuring sustainable operation of combined cycle power plants. *Journal of Cleaner Production*, 108:232–246, 2015.

[38] J. Liu, H. Liu, X.L. Yao, and Y. Liu. Evaluating the sustainability impact of consolidation policy in china's coal mining industry: a data envelopment analysis. *Journal of Cleaner Production*, 112:2969–2976, 2016.

[39] T. Baležentis, T. Li, D. Streimikiene, and A. Baležentis. Is the lithuanian economy approaching the goals of sustainable energy and climate change mitigation? evidence from dea-based environmental performance index. *Journal of Cleaner Production*, 116:23–31, 2016.

[40] T. Schoenherr and S. Talluri. Environmental sustainability initiatives: A comparative analysis of plant efficiencies in europe and the us. *IEEE Transactions on Engineering Management*, 60(2):353–365, 2013.

[41] G. Egilmez and Y.S. Park. Transportation related carbon, energy and water footprint analysis of us manufacturing: An eco efficiency assessment. *Transportation Research Part D: Transport and Environment*, 32:143–159, 2014.

[42] X. Tianqun and C. Yuepeng. Eco efficiency assessment of wuhan based on data envelopment analysis approach. In *The 27th Chinese Control and Decision Conference (2015 CCDC)*, pages 2237–2242. IEEE, 2015.

[43] B. Lahouel. Eco efficiency analysis of french firms: a data envelopment analysis approach. *Environmental Economics and Policy Studies*, pages 1–22, 2015.

[44] M. Noori and O. Tatari. Development of an agent based model for regional market penetration projections of electric vehicles in the united states. *Energy*, 96:215–230, 2016.

[45] G. James, D. Witten, T. Hastie, and R. Tibshirani. *An introduction to statistical learning*, volume 6. Springer, 2013.

[46] N.Adler and B.Golany. Evaluation of deregulated airline networks using data envelopment analysis combined with principal component analysis with an application to western europe. *European Journal of Operational Research*, 132(2):260–273, 2001.

[47] R.J. Basu, R. Bai, and P.L.K. Palaniappan. A strategic approach to improve sustainability in transportation service procurement. *Transportation Research Part E: Logistics and Transportation Review*, 74:152–168, 2015.

[48] R. Dominguez, S. Cannella, and J.M. Framinan. On returns and network configuration in supply chain dynamics. *Transportation Research Part E: Logistics and Transportation Review*, 73:152–167, 2015.

[49] G. González-Rodríguez, A. Colubi, and M.Á. Gil. Fuzzy data treated as functional data: A one way anova test approach. *Computational Statistics & Data Analysis*, 56(4):943–955, 2012.

[50] R. Lowry. One way anova-independent samples. *Vassar. edu*, 2008.