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Socio-Eco-Efficiency Analysis of Highways: A Data Envelopment Analysis

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Abstract

To ensure the large network of highways is performing sustainably, there is a dire need to quantify sustainability for highways. In this paper, data envelopment analysis (DEA) based mathematical model is developed to evaluate sustainability in an attempt to aid these efforts. Sustainability goals pertaining to the three dimensions of sustainability, social, economic and environmental, were utilized. Utilizing the developed model, sustainability scores of thirty highway sections were calculated and ranked accordingly. Percent improvement analysis was carried out to gain more insight. In addition, sensitivity analysis was carried out to understand how different values of input parameters impacted the socio-eco-efficiency of each highway section. The aim of the study was to show that DEA based sustainability assessment model could be used to evaluate highways and assist in strategic planning goals of transportation agencies. Results indicated that

Keywords: Data Envelopment Analysis; Sustainable development; Socio-Eco-efficiency; Highways.

1. Introduction

Rising urbanization worldwide brings challenging problems to governments and stakeholders thus societies due to the fact that more and more people migrate to urban areas and projections indicate that more than 60% of world population will be living in the urban areas by 2030 (Shcherbakova, 2010). In fact, the rapidly increasing trend in urban growth causes similar pattern of behavior in transportation activities. Therefore, roads of the urban areas become an integral element of sustainable development. If societies and governments fail to develop economically viable, socially acceptable and environmentally benign strategies to stabilize the worsening trends, significant amount of the carrying capacity of earth will be lost, which is expected to cause severe problems worldwide. In this regard, since highways are the principle means of transportation in urbanized areas, sustainability assessment initiatives have to be taken towards decreasing social and environmental problems that come along with and increasing the economic outputs in this problem domain as well.

The United States has the world's largest and busiest network of highways (USDOT, 2008). Maintaining this vast system while maximizing user safety and minimizing its environmental impact is of critical importance. To ensure the highways are performing to this ability, there is a dire need to quantify sustainability for highways. The vital need for sustainability metrics has been acknowledged by the Nation's leading scientific and industrial organizations. For instance, the need for a scientific evaluation framework for evaluating and integrating the life cycle environmental and economic performance of the nation's infrastructure has also been emphasized as a critical research agenda by the National Science and Technology Council (2008). Yet, there are many challenges related to quantifying the abstract concept of sustainability of highways. There is still a lack of a standard methodology for sustainability evaluation (López and Monzón, 2010). The primary difficulty lies in objectively evaluating environmental, social, and economical dimensions and the sub-categories within each dimension.

Several studies have been conducted to evaluate highway sustainability utilizing multi-criteria decision making (MCDM) approaches. Jeon et al. (2007) applied MCDM approach to evaluate transportation and land use plans in the Atlanta region in terms of comprehensive sustainability parameters. Ramani (2008) utilized Multi-Attribute Utility Theory methodology to evaluate sustainability. The way how multi-criteria evaluation approaches tackle the sustainability assessment problem is that they combine information from several criteria so as to form a single index of evaluation, which is mostly proposed as a function which is based on assignment of subjective weights by experts. Therefore, such approaches are based on expert judgment.

Most studies combine different aspects of sustainability by introducing subjective weightings or assigning equal weights to all criteria considered in their sustainability framework (Amekudzi et al., 2009; Ramani et al., 2008). Yet, there is neither a consensus nor a satisfactory method to guide the assignment of weightings (Ding, 2008). Thus, a theoretical framework which does not require *a priori* determined weightings might be useful in determining a single score for sustainability. Data Envelopment Analysis (DEA), a linear programming based mathematical modeling approach, could be a good candidate to accomplish this task, since it does not require the use of subjective weightings to rank the sustainability scores of highway sections. This methodology has already been used by several researchers in similar studies. Färe et al. (2004) provided a formal index number that can be computed using DEA techniques. Kuosmanen and Kortelainen (2005) used DEA approach to assess eco-efficiency of road transportation in Finland. Ozbek et al. (2010) used data envelopment analysis to measure the overall efficiency of road maintenance operations while considering the effects of environmental and operational factors on the overall efficiency.

The objective of this paper is to develop an analytical tool that can be used to evaluate the sustainability of highways utilizing DEA. Performance Indicators of highways are used to derive sustainability ratios and DEA is used to rank the highway sections with respect to sustainability, accordingly. The rest of the paper is organized as follows. First, the methodology is presented. Results and discussion are then presented. Finally, the findings are summarized and limitations and future work are pointed out.

1. Methodology

The methodology of the study is broken into four steps. First, we derive sustainability score in a ratio format. Second, we select the appropriate economic, social and environmental indicators. Third, we collect the appropriate data from the public records of Oregon Department of Transportation. Lastly, we develop the appropriate DEA models for the current study.

1.1. Derivation of Sustainability Ratio

Highway sustainability has been used to refer to maximizing the highway system's quality of service while minimizing its potential adverse effects on sustainability (Ramani et al., 2008). It has mostly been analyzed using three dimensions, the triple bottom line; economic, environmental, and social equity (Barbier, 2009; Graedel and Allenby, 2009; Mihelcic et al., 2003). Literature on transportation sustainability has focused on these three dimensions of sustainability, as well (Hall, 2006; Johnston, 2008; Litman, 2005, 2007; Richardson, 2005). Many indicators have been proposed to measure these three dimensions. For instance, Litman (2007) and Jeon and Amekudzi (2005) provided an extensive list of indicators that pertain to transportation sustainability dimensions. On the other hand, Ramani et al. (2008) identified five goals to reach highway sustainability: reduce congestion, enhance safety, expand economic opportunity, improve air quality, and increase the value of transportation assets. Similarly, Richardson (2005) identified five major areas that need to be monitored for more sustainable highways: safety, congestion, fuel consumption, vehicle emissions, and access.

While many indicators have been suggested to be included in the assessment of highway sustainability, different strategies have been utilized to combine the indicators to arrive at a single sustainability score. Typically, the sustainability score is derived by adding the weighted index values of the indicators from each impact category (e.g. economic, social impacts) into a composite sustainability index (Jeon et al., 2007):

$$U_i = \sum_{j=1}^{n} \left(w_j * r_{ij}\right) \tag{1}$$

where the sustainability score is conceptualized as the weighted *(w_j)* average of the indicators *(j)* considering the impacts *(r_{ij})* three sustainability dimensions *(i)*. In this regard, economic value added is the economic benefits of the system or unit analyzed. While this approach is successful in deriving a single score, it does not capture the balancing relationship between these indicators and the weight assignment is bias where priorities might change among different stakeholders. The sustainability score is often determined with respect to economic, social and environmental impacts. Economy is an important pillar for sustainable development of our nation so that the transportation systems. Therefore, the economic indicators of a transportation system is directly associated with their potential impact on expanding the economic opportunity for a nation. Towards improving economic dimension of sustainable development, the indicators that increase the economic growth directly or indirectly are desired to be maximized. Besides, social impacts of transportation activities can be also refer to the characteristics that can improve the travelers' safety and mobility (e.g. travel time, traffic crashes, etc. In this context, minimizing the negative social impacts such as travel time, traffic crashes can have a considerable impact on the sustainability performance. And, the environmental impacts such as air pollution also need to be included in assessing the sustainability score to do a comprehensive sustainability performance assessment. With regards to the environmental impacts, for instance, a busier highway might result in higher emissions, and the sustainability score needs to accurately represent the proportion of these emissions with respect to the highway load. And the direction of improvement should be towards minimizing such negative impacts to increase the sustainability performance. Conversely, in this study, following Callens and Tyteca (1999), the sustainability score is developed by taking the ratio between economic impacts, and the social and environmental impacts:

$$Highway\ Sustainability\ score = \frac{Economic\ Impacts}{Social\ and\ Environmental\ Impacts} \tag{2}$$

The derived sustainability ratio can also be termed as the *socio-eco-efficiency of highways*. In fact, this term is often addressed in sustainability literature to represent how efficient a decision making unit is in terms of the overall sustainability performance considering the social, economic and environmental aspects. While eco-efficiency analysis analyzes sustainability performance of a DMU based on economic benefits and environmental impacts (Tatari & Kucukvar, 2012); socio-eco-efficiency extends the eco-efficiency concept to the triple bottom-line sustainability score by including the social aspects of sustainability performance. The ratio approach helps to evaluate maximization of the positive economic impacts while minimizing the negative social and environmental impacts.

This sustainability ratio is based on the eco-efficiency concept, which has emerged as an alternative tool to combine environmental and economic performance indicators. Eco-efficiency ratio focuses on delivering competitively priced goods and services that satisfy human needs and enhance the quality of life, while making the efforts to reduce the environmental and ecological impacts throughout product life cycles (Kibert, 2008). It is a concept that can provide a useful framework which includes most of the principles of sustainable development to aid in decision making for infrastructure projects. Eco-efficiency analysis has been used successfully as a valuable assessment tool towards the target of sustainable development (Barba-Gutiérrez et al., 2009; Korhonen and Luptacik, 2004; Kuosmanen and Kortelainen, 2005).

1.2. Selection of Operational Variables

The most common goals cited in the literature that address the three dimensions of sustainability were utilized in this study: improve freight transport, maintain highway system quality, improve mobility, improve safety, reduce adverse human health impacts, and reduce greenhouse effect (See Table 1). Although some of these objectives could be categorized under more than one sustainability dimension, the most dominant one is chosen. For each particular objective, one measurable indicator was selected based on the literature (Jeon et al., 2007; Litman, 2007; Ramani et al., 2008; Richardson, 2005).

Table 1 Selected Highway Sustainability Objectives and Indicators

Dimension	Objective	Indicator	Acronym	References
Economic	Improve freight transport	Truck throughput efficiency (mph)	TTE	(Litman, 2007; Ramani et al., 2008)
	Maintain highway system quality	Pavement condition score	APC	(Litman, 2007; Ramani et al., 2008)
Social	Improve mobility	Travel time Index	TTX	(Jeon et al., 2007; Ramani et al., 2008; Richardson, 2005)
	Improve safety	Annual Crashes/mile	ACM	(Jeon et al., 2007; Ramani et al., 2008; Richardson, 2005)
Environmental	Reduce adverse human health impacts	NO_x, CO, and VOC* emissions (mT)	NCV	(Jeon et al., 2007; Ramani et al., 2008; Richardson, 2005)
	Reduce greenhouse effect	Daily CO_2 emissions (mT)	CO2	(Jeon et al., 2007; Ramani et al., 2008; Richardson, 2005)
	Reduce traffic noise	Average Noise Level (dBA)	ANL	(Jeon et al., 2007; Ramani et al., 2008; Richardson, 2005)

In terms of economic indicators, expanding economic opportunity and increasing the value of transportation assets could be achieved by improving the road based freight movement and maintaining the quality of the existing highway system. To measure these objectives, truck throughput efficiency (TTE) and average pavement condition (APC) score are utilized, respectively. Freight movement is a key economic benefit of highways and hence needs to be maximized. Truck throughput efficiency measures truck volumes and speeds as an output combination as shown in Equation 3.

$$TTE = Daily\ truck\ volumes\ per\ lane \times Truck\ operational\ speed \tag{3}$$

APC score measures the quality of maintenance of a section of the highway road, and gives a good indication regarding the value of transportation assets. APC is scaled between 0 and 100, as a road condition score which is a combination of various factors including surface distress, rutting, and ride quality. APC scores are directly obtained from Oregon DOT's databases.

Reducing congestion and enhancing safety by improving mobility on highways and reducing crash rates and crash risk are chosen as key indicators to measure the social impact of the highways. Travel time index

(TTX) and annual severe crashes per mile are utilized as the respective performance indicators. TTX measures the extent of delays caused in travel due to traffic congestion alone and annual severe crashes per mile measures the crash rate on highways. TTX is calculated via Equation 4 (Ramani, et al., 2008).

$$\text{Travel Time Index (TTX)} = \frac{\text{Peak Hour Travel Rate (Minutes per Mile)}}{\text{Travel Rate at Posted Speed Limit (Minutes per Mile)}} \tag{4}$$

The peak hour travel rate is calculated by using the procedure provided in TTI's Urban Mobility Report (Schrank and Lomax, 2009). The procedure determines the peak-period vehicle operating speeds based on the average daily traffic (ADT) per lane. The peak period speed guidelines are provided in Table 2.

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Table 2 Peak Period Speed Guidelines

ADT per Lane	**Peak Period Speed (PPS)**
15001-17500	PPS=70-(0.9*ADT/Lane)
17501-20000	PPS=78-(1.4*ADT/Lane)
20001-25000	PPS=96-(2.3*ADT/Lane)
ADT/Lane>25000	PPS=76-(1.46*ADT/Lane)

On the other hand, improving air quality, conserving natural resources and reducing traffic noises are chosen as key indicators to measure the environmental impacts of highways. Daily NO_x, CO and VOC emissions per mile of the highway, daily CO_2 emissions per mile of highway and average noise level (ANL) are utilized as the respective performance indicators. NO_x, CO and VOC are weighted according to their relative damage costs in terms of human health impacts. CO_2 emission is associated with global warming and it is measured in grams per mile of highway. ANL values are calculated as follows.

The average noise levels (ANLs) on the selected highways were calculated iteratively by using equations (5,6 and 7) (Abbott & Nelson, 2002); (Horoshenkov, 2012). In this regard, first the basic road noise level is predicted (Eq. 5). Then, the correction factor for traffic speed, percent of heavy vehicles and gradient is calculated (Eq.6). Finally, the impact of road surface on the road noise levels was captured with Eq. 7. The overall noise level prediction is performed by considering traffic speed, percent of heavy vehicles and road surface impact. Due to macro level data availability issues, the effect of gradient and other road characteristics such as size of size of segments, site layout are neglected.

$$L_{10}(18\,hr) = 29.1 + 10 * log_{10}(Q), dBA \quad (5)$$

where Q is the 18-hour traffic flow (vehicles/hour) with assumption of V=75/km/h, percentage of heavy vehicles p=0 and gradient is zero (G=0).

Correction for mean traffic speed, percentage of heavy vehicles and gradient:

$$\Delta_{pV} = 33 * log_{10}\left(V + 40 + \frac{500}{V}\right) + 10 * log_{10}\left(1 + \frac{5p}{V}\right) - 68.8, dBA \quad (6)$$

The percentage of heavy vehicles is given by$p = \frac{100*F}{Q}$, where F is the 18-hour flow of heavy vehicles.

Moreover, road surface impact is calculated as follows.

$$\Delta_{TD} = 10 * log_{10}(20 * TD + 60) - 20, dBA \quad (7)$$

where TD is the texture depth.

1.3. Data Collection

Highway sections were selected as the functional unit to carry out the study. Public data sources in the Oregon Department of Transportation (ODOT) website were used to collect data for thirty interstate highway sections (2010). Six indicators were utilized for sustainability measurement (see Table 3). TTX for each highway section was calculated based on Texas Transportation Institute's Urban Mobility Report (Schrank and Lomax, 2009). Data for annual crashes per mile were gathered from ODOT's crash rate tables (ODOT, 2008). TTE was calculated using equations from Ramani et al's study (2008). Truck volume was gathered from ODOT's traffic volume and vehicle classification online database. Average pavement condition data was extracted from ODOT's website. National Mobile Inventory model (NMIM) software was used to calculate CO_2, CO, NO_x, and VOC emissions for the highway sections. CO, NO_x, and VOC emissions were weighted according to their relative damage costs in terms of human health impacts based on U.S. DOT's report on highway economic requirements system (Ramani et al., 2008; USDOT, 2002). Noise data is obtained via using equations 5, 6 and 7 and average traffic speed, daily traffic and road surface data obtained from ODOT's traffic volume and vehicle classification online database.

Utilizing DEA Models for Evaluating Highway Sections

The socio-eco-efficiency ratios were calculated for each highway section by utilizing DEA. DEA is a non-parametric method that got its birth from the work of Charnes, Cooper and Rhodes (1978). It is a linear programming methodology that measures the efficiency of multiple Decision Making Units (DMUs) when there are multiple inputs and multiple outputs with different units (Sarkis, 2007). DMUs are directly compared against peers or a combination of peers. DEA assesses how well a DMU is performing compared to other DMUs, by maximizing the output or minimizing the input of the studied DMUs. The basic concept of efficiency measurement was originally developed based on the ratio of total outputs to total inputs.

Table 3 Descriptive Data of Highway Sections

Highway Section Information								Economic		Social		Environmental		
No	Route	Rd. ID	Region	District	County	County ID	Name	TTE	APC	TTX	ACM	CO2	NCV	ANL
1	I-5	1	3	08	Jackson	29	California State Line - Ashland	85463.63	88	1.15	2.01	5543.46	21.21	66.94
2	I-5	1	3	08	Josephine	33	N. Grants Pass – Jump off Joe Creek	103576.72	49	1.71	1.48	3115.63	13.69	67.58
3	I-5	1	3	07	Douglas	19	Winchester Intch - Sutherlin	132681.71	97	1.86	0.96	3757.61	15.81	67.55
4	I-5	1	2	05	Lane	39	Goshen - Willamette R.	179377.38	57	1.86	3.49	5801.45	22.97	70.61
5	I-5	1	2	04	Lynn	43	N. Albany - S. Jefferson	202381.53	99	1.86	4.03	5762.84	24.41	70.49
6	I-84	2	1	02B	Multnomah	51	I-5/I-84 Interchange Section	138923.07	70	1.86	13.75	11546.27	32.6	74.98
7	I-84	2	1	02C	Multnomah	51	Corbett - Multnomah Falls	113531.44	83	1.69	1.6	11546.27	32.6	67.13
8	I-84	2	4	09	Wasco	65	Rowena - The Dalles	93024.75	64	1.36	1.46	2856.06	12.33	67.71
9	I-84	2	5	12	Morrow	49	Tower Rd-Boardman	69898.4	56	1	0.48	2112.06	8.67	67.6
10	I-84	6	5	12	Umatilla	59	Stanfield Intch - Pendleton	62619.86	82	1.15	0.48	2387.19	9.74	66.94
11	I-84	6	5	13	Union	61	Hilgard - Lower Quarry Bridge	76384.17	63	1	0.79	2518.49	10.52	66.88
12	I-84	6	5	13	Baker	1	South Baker - Encina	60005.09	99	1	1.04	1076.86	4.84	65.42
13	I-84	6	5	14	Malheur	45	Malheur R. - Snake R.	54469.12	60	1	0.66	3970.88	17.62	67.6
14	I-405	61	1	02B	Multnomah	51	Fremont Bridge Section	179359.05	97	1.86	16.91	11546.27	32.6	74
15	I-205	64	1	02B	Multnomah	51	Abernathy Br - Uprr O-Xing	191530.17	94	1.86	9.35	11546.27	32.6	73.91
16	I-82	70	5	12	Umatilla	59	Columbia Rvr - Hwy 002 O-Xing	76110.74	73	1.19	3.23	2387.19	9.74	67.6
17	I-82	70	5	12	Umatilla	59	Hwy 002 O-Xing - Jct Hwy 006	56748.15	89	1	0.29	2387.19	9.74	66.01
18	I-105	227	2	05	Lane	39	Willamette R. - Coburg Rd	46833.15	98	1.86	3.33	5801.45	22.97	70.42
19	I-5	001	3	3	Jackson	29	Jackson St - Seven Oaks	101303.8	63	1.86	1.28	5543.46	21.21	69.15
20	I-5	001	3	3	Douglas	19	Canyonville - Myrtle Creek	96690.75	79	1.69	1.22	3757.61	15.81	67.13
21	I-5	001	3	3	Douglas	19	Elkhead Rd - Anlauf	117050.8	78	1.36	1.42	3757.61	15.81	67.39
22	I-5	001	2	2	Marion	47	N. Santiam Hwy - State St	244644.4	97	1.86	2.81	3970.88	17.62	72.08
23	I-5	001	2	2	Marion	47	Baldock Sra - Willamette R. (Reg 2)	198941.6	90	1.86	2.27	3970.88	17.62	72.25
24	I-5	001	1	1	Washington	67	Hassalo St - Stadium Fwy	224082.72	82	1.86	9.94	2856.06	12.33	74.04
25	I-84	002	1	1	Multnomah	51	Ne 181st Ave Intch	134627.74	66	1.86	5.73	11546.27	32.6	72.76
26	I-84	002	1	1	Hood River	27	Cascade Locks - Mitchell Point	79408.62	76	1.43	0.92	3757.61	15.81	67.33
27	I-84	002	4	4	Sherman	55	Rufus - Swanson Canyon	61413.14	64	1	0.6	11546.27	32.6	66.88
28	I-84	006	5	5	Baker	1	La Grande - Ladd Canyon (Pcc)	62273.43	50	1	4.44	1076.86	4.84	66.42
29	I-84	006	5	5	Baker	1	Durkee - Bubbs Ranch	71869.79	52	1	1.98	1076.86	4.84	65.81
30	I-84	006	5	5	Malheur	45	Huntington O'xing - Farewell Bend	73223.77	84	1	0.67	3970.88	17.62	65.54

Units of measurement: TTE (truck-miles per hour per lane), APC (dimensionless), TTI (dimensionless), ACM (severe crashes per mile per year), CO2 (grams per mile per day), NCV (grams per mile per day), ANL (Average Noise Level, A-weighted decibels (dBA))

An example is provided below (See Table 4) to illustrate the basic concept behind DEA methodology. Suppose that there are three companies to be compared among each other based on how efficiently they produce total economic output (total outputs) from the total fixed and working capitals (total inputs). The economic value added per capital invested ratios simply represents their efficiency measurements where company A performs the best and is on the efficiency frontier. Therefore, setting company A's performance efficiency at 100%, the remaining two companies' efficiency scores become 94.3% and 75.0%.

Table 4 Efficiency Score Example

Performance of Three Companies				
Company	Total Inputs	Total Outputs	Economic Value Added per Capital Invested	Efficiency Score
A	120	140	1.17	100.0%
B	100	110	1.10	94.3%
C	80	70	0.88	75.0%

DEA models can primarily be grouped into two categories; one that has constant returns to scale and another that has variable returns to scale. The constant returns to scale based linear program equation, coined by Charnes, Cooper, and Rhodes, is as follows (1978):

$$\max z = \sum_{r=1}^{s} \mu_r y_{ro} \tag{8}$$

subject to

$$\sum_{i=1}^{m} v_i x_{io} = 1 \tag{9}$$

$$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \quad j = 1, \ldots, n \tag{10}$$

$$\mu_r, v_i \geq 0 \tag{11}$$

where μ_r is the output multiplier, v_i is the input multiplier, o is the DMU under evaluation, s represents the number of outputs, m represents the number of inputs, n represents the number of decision making units,

y_{rj} represents the amount of output r produced by DMU j, and x_{ij} represents the amount of input i used by DMU j. The objective function z is the weighted sum of outputs for the DMU under evaluation.

A DEA model works by running the linear programming model for each DMU so as to compare one with the rest of the DMUs. The DMU with the maximum output and minimum input is considered as on the efficiency frontier based on which other DMUs' efficiency scores were relatively determined. The variable returns to scale (VRS) based linear program equation, coined by Banker, Charnes, and Cooper, is as follows (1984):

$$\max z = \sum_{r=1}^{s} \mu_r y_{ro} + w \tag{12}$$

subject to

$$\sum_{i=1}^{m} v_i x_{io} = 1 \tag{13}$$

$$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + w \leq 0 \quad j = 1, \ldots, n \tag{14}$$

$$\mu_r, v_i \geq 0 \tag{15}$$

where μ_r is the output multiplier, v_i is the input multiplier, o is the evaluated DMU, s represents the number of outputs, m represents the number of inputs, n represents the number of decision making units, y_{rj} represents the amount of output r produced by DMU j, x_{ij} represents the amount of input i used by DMU j and w is the scale weight. The objective function z is the weighted sum of outputs for the DMU under evaluation. In addition, w represents the dual form of convexity constraint of input-oriented envelopment model (Thanassoulis, 2001).

DEA model may take different forms by manipulating the objective function and adding different restrictions. It is critical to choose the suitable DEA model for the purpose of the study. The complexity that lies within DEA is to accurately select the right DEA strategy. This strategy depends on whether the studied phenomena can be modeled as a constant return to scale or variable return to scale. In VRS, the output does not increase by the same proportional change for each proportional increase in the input. On the other hand, CRS is a special case of the variable returns to scale in which the output increases by the same proportional change for each proportional increase in the input (Ozbek et al., 2010). Fig. 1 illustrates the difference between CRS and VRS. From the CRS perspective, if the efficiency frontier is set based on company A, then even though companies B and C performs well depending on their greater input scales, their relative efficiency value are going to be far lower than the 100%. To prevent this scale effect on efficiency scores, the variable returns to scale (VRS) property was included in DEA models so as to take scale difference into consideration.

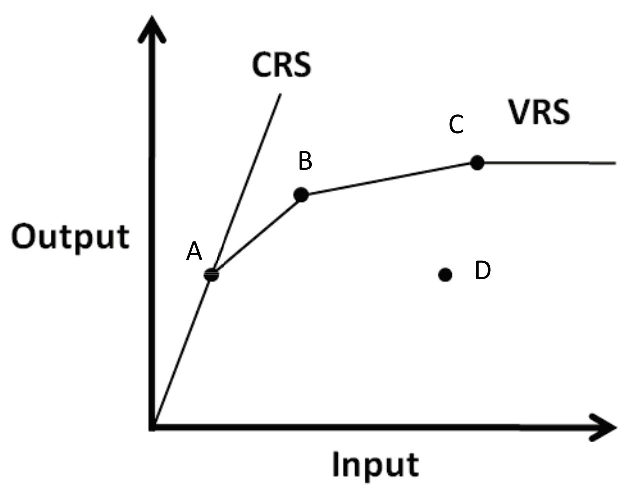

Fig. 1 CRS vs. VRS Efficiency

Once the type of the model is selected it is necessary to decide on the orientation (i.e. input oriented or output oriented). This decision is based on whether we want the input reduced or the output increased in the process. DEA methodology has been utilized by several researchers to evaluate the environmental performance of DMUs. Typically, environmental indicators have been considered as either undesired inputs or outputs in the DEA framework (See Färe et. al (1989) and Tyteca (1997)). On the other hand, Kuosmanen and Kortelainen (2005) utilized DEA approach to assess eco-efficiency of road transportation in Finland. Their approach deviated from the typical DEA approaches that have analyzed environmental impacts as secondary inputs or outputs. Instead, input and outputs that are not in direct interest in the framework were omitted. Callens and Tyteca (1999) and Tyteca (1999) utilized DEA to account for economic, social, and environmental indicators. In this approach, the indicators are utilized to compare DMUs that produce similar products within a specified time period. Indicators that should be minimized or maximized in order to reach sustainable efficiency are chosen. In this approach, undesirable inputs or outputs are minimized against the desirable inputs or outputs. This approach has been adopted for the current study and applied to the context of highway sustainability.

The general DEA framework in modeling the socio-eco-efficiency of highways is as follows: Social and environmental indicators act as inputs and economic indicators act as outputs. The DMU is represented as a highway section, where for each section there are two outputs and four inputs. The representation of highway sections as DMUs is similar to the study that was conducted by Cook et. al (2001). Triantis (2004) surveys the engineering applications of DEA, where DMU has been defined more appropriately as the unit of analysis in the engineering context. VRS approach was chosen for the current study, since there are large differences in the ADT and truck throughput between highway sections that are assumed to have non-constant return to scale with respect to the environmental and social indicators. This approach accounts for possible scale diseconomies that can exist between highways in different regions. Based on equation (7), the developed DEA model at time t is as follows:

$$\max z = aTTE_o + bAPC_o + w \tag{16}$$

subject to

$$cTTI_o + dACM_o + eNCV_o + fCO2_o = 1 \tag{17}$$

$$(aTTE_j + bAPC_j) - (cTTI_j + dACM_j + eNCV_j + fCO2_j) + w \leq 1 \quad j = 1, \dots, n \tag{18}$$

$$a, b, c, d, e, f \geq 0 \tag{19}$$

where a, b, c, d, e, and f are weights that are determined by the solution of model, *w* is the scale weight, *o* is the DMU which is being evaluated, *n* is the number of DMUs, and TTE, APC, TTI, ACM, NCV, and CO2 represent the corresponding indicator values for each DMU. The above LP model was solved eighteen times; one for each DMU. For each DMU, the LP searches for a linear combination of other highway sections in the sample to produce a greater level of output with fewer inputs.

2. Results and Discussion

Fig. 2 shows the results of benchmarking model in terms of socio-eco-efficiency scores in percentages. The socio-eco-efficiency scores for the highway sections ranged from 0.65 to 1. Results indicated that only nine highway sections (HS-30, HS-3, HS-22, HW-5, HS-29, HS-24, HS-9, HS-12 and HS-17) were found to be 100% socio-eco-efficient compared to the other highway sections. HS-25 was found to be the least efficient (65%). The average efficiency score is obtained as 86.5% with a standard deviation of 12.2%.

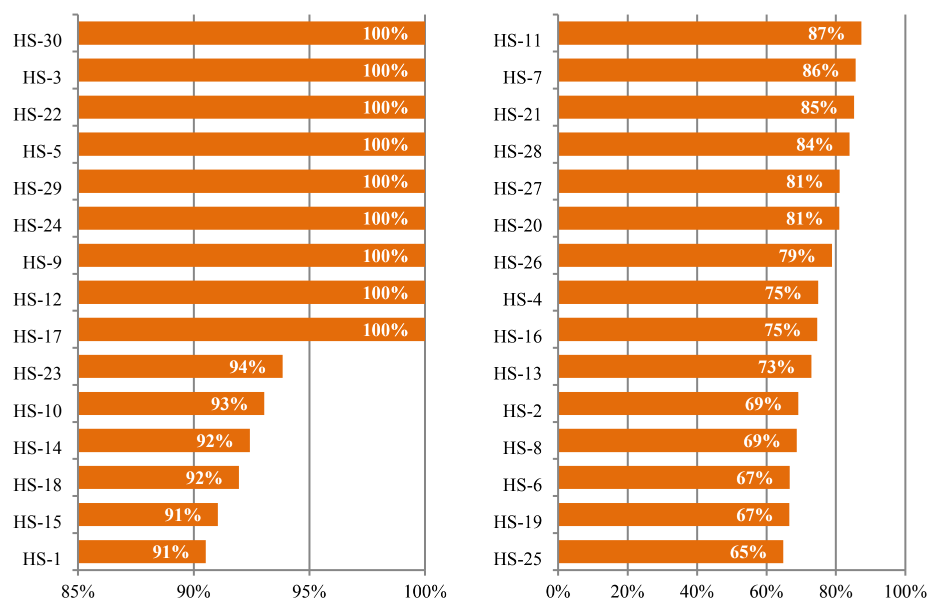

Fig. 2 Socio-economic Efficiency Scores

Although, it is important to evaluate the relative socio-efficiency of the highway sections with the proposed linear programming-based benchmarking model, there is a need to quantify the potential improvements that can be achieved by inefficient highways to be 100% efficient. For inefficiency highway sections, the potential improvements can be achieved via reducing the negative environmental and social impacts while keeping the economic outputs the same. Table 5 shows the percent reductions in five input variables for each highway section to become 100% efficient. For instance, for HS-23 to reach 100% efficiency, it needs to reduce TTX by 6.2%, ACM by 53.2%, CO2 by 7.5%, NCV by 8.9% AND ANL by 6.2%. It is worth to note that HS-18 *(46.8%)*, HS-2 *(39.3%)*, and HS-25 *(35.2%)* required the greatest reductions in TTX. For ACM, HS-6 *(83.1%)*, HS-14 *(79.0%)* and HS-18 *(69.1%)* required the highest amounts of reductions. For CO2, HS-27 *(83.7%)*, HS-18 *(81.6%)*, and HS-1 *(73.6%)*; for NCV HS-18 *(79.1%)*, HS-27 *(76.0%)*, and HS-1 *(69.2%)* and for ANL, HS-28 *(44.8%),* HS-2 *(42.4%)* and HS-25 *(35.2%)* required the highest amounts of reductions. It is important to note that the nine efficient highway sections mentioned above did not need any improvement in reducing their social and environmental indicators, since they were found to be 100% efficient.

INSERT TABLE 5

Table 5 Target Reductions in Input Variables (%)

Highway	TTX	ACM	CO2	NCV	ANL
HS-23	-6.2%	-6.2%	-7.5%	-8.9%	-6.2%
HS-10	-10.9%	-6.9%	-8.0%	-6.9%	-6.9%
HS-14	-8.2%	-79.0%	-56.5%	-34.6%	-7.6%
HS-18	-46.8%	-69.1%	-81.6%	-79.1%	-8.0%
HS-15	-9.0%	-65.6%	-60.7%	-40.2%	-9.0%
HS-1	-9.5%	-38.6%	-73.6%	-69.2%	-11.1%
HS-7	-14.6%	-14.3%	-73.0%	-59.5%	-14.3%
HS-21	-14.8%	-14.8%	-33.0%	-31.5%	-14.8%
HS-20	-21.5%	-19.0%	-30.5%	-30.0%	-19.0%
HS-26	-21.2%	-21.2%	-42.9%	-42.6%	-21.2%
HS-4	-26.7%	-41.0%	-49.8%	-43.8%	-25.2%
HS-16	-25.4%	-66.8%	-45.8%	-40.7%	-26.6%
HS-11	-12.7%	-12.7%	-21.3%	-20.6%	-27.9%
HS-27	-19.0%	-19.0%	-83.7%	-76.0%	-28.2%
HS-8	-31.3%	-31.3%	-32.1%	-32.1%	-31.3%
HS-13	-27.1%	-27.1%	-36.5%	-37.3%	-31.8%
HS-6	-33.3%	-83.1%	-71.6%	-56.9%	-33.3%
HS-19	-33.4%	-33.4%	-54.4%	-49.3%	-33.4%
HS-25	-35.2%	-58.2%	-70.5%	-55.4%	-35.2%
HS-2	-39.3%	-30.9%	-30.9%	-32.0%	-42.4%
HS-28	-30.6%	-50.7%	-16.1%	-18.0%	-44.8%

Finally, a sensitivity analysis also conducted to evaluate the impact of each input variable on the socio-economic efficiency score. Fig. 3 presents the sensitivity of each input indicator on the socio-eco-efficiency of inefficient highway sections along with the average target reduction (%) values. In this regard, the sensitivity results enable us to understand the magnitude of change in the efficiency score as a result of the relative change in the input variables (social and environmental indicators).

For example, TTX was found to have the highest sensitivity ratio for HS-1 (93%). This was followed by ACM, CO2, and NCV, respectively (33%, 25%, and 29%). It is important to note that ANL and TTX was found to have the highest average sensitivity ratio for the selected highway sections. The high sensitivity of this indicators means that a small reduction would have a higher impact on the overall socio-eco-efficiency compared to other indicators. On the other hand, the average target reductions represent a reverse trend compared to sensitivity values. The greatest reductions were suggested on CO_2 *(46.7%)* and NCV *(41.2%),* which indicated relatively smaller sensitivity values. This result provides significant insights about the research conducted. For inefficient states to become 100% efficient, smaller reductions in TTX and ANL can have more significant improvement on the socio-economic efficiency scores.

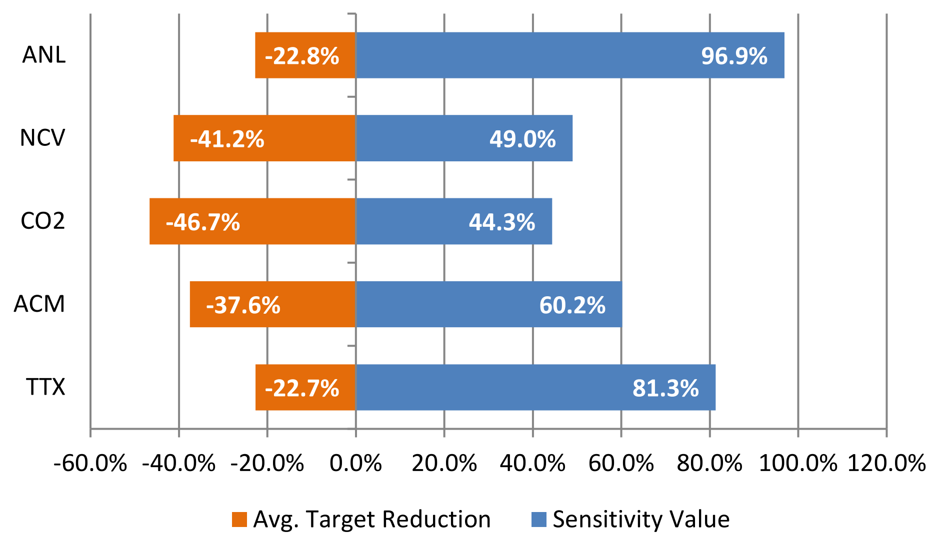

Fig. 3 Sensitivity Analysis vs. Average Target Reduction (%)

3. Conclusions

In this paper, a DEA based sustainability assessment tool is developed to evaluate highways. The model used economic, social, and environmental indicators to calculate sustainability performance and result in scores for Oregon state highways. Seven sustainability goals that pertain to sustainability were utilized: improve freight transport, maintain highway system quality, improve mobility, improve safety, reduce adverse human health impacts, reduce greenhouse effect and reduce traffic noise. Results from the model showed that HS-30, HS-3, HS-22, HW-5, HS-29, HS-24, HS-9, HS-12 and HS-17 were 100% sustainable. Percent improvement analysis was carried out to find out the amount of reduction needed in the social and environmental parameters to reach 100% sustainability. Results of percent improvement analysis indicated that 22% to 47% reductions are required to be achieved on negative social and environmental impacts for the inefficiency highway sections to be 100% efficient while keeping the economic indicators the same. In addition, sensitivity analysis was conducted to understand how significant the different values of input parameters impacted the socio-eco-efficiency score of each highway section. An average of 44% to 97% sensitivity range is observed on the highway sections depending on the input variable.

The analysis of DEA results could be very helpful to state highway agencies to compare the relative sustainability of highways. However, it should be noted that DEA compares the sustainability of highway sections by analyzing other sections in the data set. This is a major drawback of DEA, since the sustainability scores are relative to the sustainability of the highway sections in the data set. Also, accuracy of the results depends on the accuracy of the data extracted. Taking these limitations into consideration, the developed DEA-based sustainability assessment model can be used by transportation agencies to evaluate highways within their jurisdiction. It not only provides immediate assessment of sustainability but also helps provide feedback to actually develop more sustainable planning goals in the future. In future work, enlargement of the data set to include most state-wide highway inventory is planned in order to produce more generalized sustainability scores. This highway inventory could extend to include different states and larger regions, as well.

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