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A Fuzzy and a Monte Carlo simulation approach to assess sustainability and rank vehicles in urban environment

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Abstract

The selection and assessment of new vehicle technologies and mobility solutions to stimulate sustainable transportation planning becomes challenging, due to lack of frameworks and tools that are capable of considering the features of new solutions. The objective of this paper is to present a method that combines Fuzzy Logic and Monte Carlo Simulation (MCS) for the sustainability assessment of urban transportation vehicles and evaluate the applicability of the method to selected indicators for ranking the sustainability performance of vehicles. The fuzzy method has been chosen for its ability to incorporate imprecise and vague information in a decision-making process and the MCS for its ability to generate many scenarios by considering the random sampling of each probability distribution of uncertain input values. The results revealed that by using the fuzzy method alone or with MCS provide similar rankings. The MCS added value to the sustainability assessment by presenting the distribution characteristics of each sustainability index for the five vehicle types and added a layer of statistical confidence in interpreting and comparing the advantages and disadvantages between vehicle types.

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1. Introduction

Transportation planning in urban areas is a complex process due to the multiple components of a transportation system that need to be taken into consideration. These components generate many and potentially large impacts because they affect travel patterns, commuting, travel behaviors, land uses etc. Selection and assessment of new vehicle technologies and mobility solutions in transportation planning to promote sustainability becomes challenging, due to lack of frameworks and tools that are capable of considering the features of new solutions.

New vehicle technologies and fuel types, with no long term data and only limited short term data, introduce uncertainty in the evaluation of new transportation modes and in the formation of environmental and transportation strategies. New vehicle and fuel features, with an unexplored impact on sustainability and transportation planning, necessitate that uncertainty should be incorporated in sustainability assessments. Additionally, the complexity of transportation systems and the numerous indicators that are developed for the assessment per se invite uncertainty

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because required data may be incomplete. Uncertainty can be treated with probabilistic methods that require data to have a statistical basis. However, some input variables in a decision making process do not have a statistical basis, therefore other methods such as the fuzzy logic are required. Fuzzy logic methods may combine vague and uncertain criteria with well-defined and/or quantitative criteria to obtain the best alternative (Hardy 1995).

In fuzzy logic, imprecise information can be represented by linguistic values that through an inference system can provide precise conclusions. Fuzzy methods are recommended for application in sustainability oriented problems because such problems include non-uniform quantities and data, uncertain information, imprecise data and interrelations between sustainability dimensions (Pislaru and Trandabat 2012; Rossi et al. 2013). The objectives of this paper are to develop and present a fuzzy and a Monte Carlo Simulation approach for the sustainability assessment of urban transportation vehicles and evaluate the applicability of the method to selected indicators for ranking the sustainability performance of vehicles. The fuzzy method has been chosen for its ability to incorporate imprecise and vague information in decision making process. A Monte Carlo Simulation is also used in the calculation of the distribution percentiles of the sustainability indices for the five vehicle types by taking into account the uncertainty in of the input indicators. A recent study by Mitropoulos and Prevedouros (2013) developed a sustainability framework for assessing the sustainability performance of urban transportation vehicles using several powerplants and fuels under various scenarios. The study herein develops a fuzzy logic and Monte Carlo based method for incorporating uncertainty into sustainable transportation planning and uses the results from Mitropoulos and Prevedouros (2013) to test the method.

2. Sustainability Assessment Framework of Urban Vehicles

The proposed sustainability framework consists of five dimensions that are captured by the goals for governing transportation systems: Environment, Technology performance, Energy, Economy, and Users. The goals of the framework are to help a community meet its needs by: 1) Minimizing environmental impact and energy consumption; and 2) Maximizing its economy, user and community satisfaction, and technology performance. (Technology performance refers to the features of modes that support community livability, enhance public health, safety and comfort for all their users.) A set of indicators was developed for assessing the sustainability performance of five urban transportation vehicles based on the framework's five dimensions. The indicators address objectives by identifying individual vehicle features that contribute towards maximization of sustainability. When the impacts (i.e., positive or negative) of those features of sustainability are aggregated for all vehicles on the network, their value determines goal achievement and ways to move a transportation system towards sustainability. The sustainability framework was the methodological guide for developing a sustainability assessment tool.

All vehicles were assumed to use the same highway infrastructure; roads and related traffic infrastructure were not part of the assessment. The five urban vehicles examined were: Internal Combustion Engine Vehicle (ICEV), Hybrid Electric Vehicle (HEV), Electric Vehicle (EV), Diesel Bus (DB), Hybrid Diesel Electric Bus (HDEB). Vehicle specifications were necessary for estimating their impact on the five sustainability dimensions (i.e., Environment, Technology performance, Energy, Economy and Users) that capture the goals of a transportation system. For vehicle types, such as the ICEV, the HEV and the EV, the most representative vehicles were selected based on their sales volume (Edmunds 2012). Vehicle type refers to vehicle propulsion technology (e.g., internal combustion engine, electric motor or hybrid), and basic functionality (e.g., car/van, light-truck, bus, etc.) In summary, the assumption for modelling emissions and energy indicators per life cycle stage are described below.

Manufacturing. Manufacturing emissions and energy were modeled in The Greenhouse Gases, Regulated Emissions and Energy Use in Transportation GREET (CTR 1998; CTR 2005; CTR 2006) including vehicle materials, batteries, fluids and vehicle assembly. Specific input assumptions related to each vehicle and its components are extracted from the official specifications sheet of each vehicle (e.g., vehicle weight, battery weight, fluid weight, other material percentage by weight).

Fueling. GREET is used for the fuel life cycle ("well to wheel"). The model estimates the emissions and energy associated with primary energy production (feedstock recovery), transportation and storage, and with fuel production, transportation, storage and distribution. The fuel production option for conventional gasoline and low sulfur diesel is petroleum. For electricity generation the following mix is assumed: Coal 50.4%, nuclear power 20.0%, natural gas 18.3, residual oil 1.1%, biomass 0.7%, other 9.5% (i.e., hydro, solar, wind and geothermal).

Operation and Idling. For the operation stage, MOBILE6.2 (EPA 2003) was used to estimate the emissions generated

from gasoline vehicles. Urban average speeds of 28 mph and 12 mph were used for passenger vehicles and buses, respectively (TCRP 2003; APTA 2009; TTI 2009). Energy consumption was estimated with GREET. Idling emissions were estimated based on the assumption that the 2.5 mph emission factors can be applied to the entire idling time (EPA 2003). EIO-LCA (Hendrickson et al. 2006) estimates the materials and energy resources required for and the environmental emissions resulting from economic activities.
Maintenance. Vehicle maintenance includes the maintenance and disposal of vehicle parts. GREET examines the emissions and energy associated with vehicle disposal. EIO-LCA was used to estimate the emissions and energy inventory associated with automotive maintenance and the tire manufacturing services based on maintenance costs. The quantification models and assumptions that produce the indicator estimates in Table 1 are detailed in Mitropoulos and Prevedouros (2013).

Table 1. Quantified vehicle sustainability indicators and relative indices for sustainability dimensions

Sustainability Dimension	Indicator	Units	ICEV	HEV	EV	DB	HDEB
Environment	CO_2 (w/ C in VOC & CO)*	*grams/ PKT*	336.16	180.20	211.89	203.81	161.56
	CH_4	*grams/ PKT*	0.47	0.29	0.34	0.21	0.18
	N_2O	*grams/ PKT*	0.01	0.01	0.01	0.00	0.00
	GHGs	*grams/ PKT*	351.07	189.52	221.21	211.27	169.01
	VOC	*grams/ PKT*	0.58	0.52	0.04	0.14	0.12
	CO	*grams/ PKT*	4.30	4.27	0.27	0.56	0.52
	NO_x	*grams/ PKT*	0.55	0.47	0.25	0.63	0.63
	PM_{10}	*grams/ PKT*	0.11	0.09	0.30	0.04	0.04
	SO_x	*grams/ PKT*	0.21	0.22	0.60	0.10	0.08
	Average noise level	*dB*	61	57	57	78	78
Technology Performance	Fuel frequency	*minutes/PKT*	0.008	0.006	0.015	NA	NA
	Maintenance frequency	*minutes/PKT*	0.012	0.011	0.006	0.002	0.002
	Space occupied	*m^2/passenger*	7.6	6.8	6.8	3	3.1
	Engine power	*kg m/kg*	0.015	0.015	0.018	0.011	0.007
Energy	Manufacturing energy	*Mjoule/ PKT*	0.385	0.393	0.443	0.208	0.243
	Fueling energy	*Mjoule/ PKT*	0.782	0.342	1.227	0.297	0.254
	Operation energy	*Mjoule/ PKT*	3.051	1.554	0.899	2.238	1.604
	Maintenance energy	*Mjoule/ PKT*	0.170	0.165	0.114	0.125	0.117
Economy **	Manufacturing cost	*$/PKT*	0.091	0.098	0.142	0.034	0.057
	Operation (user costs)	*$/PKT*	0.156	0.105	0.092	0.398	0.038
	Maintenance cost	*$/PKT*	0.028	0.026	0.016	0.027	0.026
	Any form of subsidy	*$/PKT*	0.000	0.000	0.034	0.168	0.168
	Cost for unreserved parking	*$/passenger*	188.9	188.9	0	0	0
Users	% of time not available for user's usage based on 24h	*hours of down time or not operable per year expressed as an annual %*	0.03%	0.02%	9.61%	20.83%	20.83%
	% of time not available for user's usage based on 19h	*hours of down time or not operable per year expressed as an annual %*	0.04%	0.03%	3.47%	0.00%	0.00%
	Passenger space	*m^3/passenger*	0.574	0.529	0.521	0.563	0.509
	Goods carrying (cargo) space	*m^3/passenger*	0.085	0.129	0.068	0.054	0.054
	Leg room front	*cm*	105.9	107.9	106.9	68.6	68.6
	Fuel frequency	*number of stations in operation*	121,446	121,446	626	NA	NA

Note (*): The carbon fraction in VOC and CO is considered in the total CO_2 emissions because carbon in VOC and CO will eventually be converted to CO_2 with further atmospheric chemical reactions (oxidation).
Note (**): All costs are converted in 2011$. All Economy indicators are assumed to have negative impact to sustainability. Indicators are perceived from users' point of view; therefore they reveal how vehicle monetary parameters may affect vehicle utilization and make sustainable or unsustainable a transportation vehicle for a chosen network.

3. Fuzzy Logic Method

The fuzzy methodology used herein to assess sustainability of urban vehicles is divided into four steps: a)

Fuzzification, b) Inference step, c) Aggregation, and d) Defuzzification. In the fuzzy sustainability assessment, the Overall Sustainability Performance per vehicle type is composed by five primary components that represent the sustainability dimensions: Environment (ENV), Technology performance (TECH), Energy (ENR), Economy (ECON) and Users (USER). Each of the primary components has inputs which are represented by the sustainability indicators. Sustainability indicators were grouped in these five sustainability dimensions. The complete fuzzy sustainability assessment method consists of Levels I and II. The output of each fuzzy method in each level is a corresponding sustainability index.

3.1. Fuzzification

At Level I, normalized input variables (i.e., sustainability indicators) are fuzzified by being transformed to linguistic values that have two fuzzy sets: "Unsustainable" (UNS) and "Sustainable" (SUS). The "UNS" is defined for normalized indicator values ranging between [0, 0.499] for which unsustainability is greater than sustainability; and the "SUS" is defined for normalized values ranging from [0.5, 1] for which sustainability is greater than unsustainability. The equivalent grade of membership for value 0.5 between unsustainable and sustainable levels reveals the uncertainty of appraising correctly the sustainability level of an indicator (Figure 1a). Similarly, primary sustainability components (i.e., ENV, TECH, ENR, ECON and USER) are defined by using linguistic values with three fuzzy sets "Low" (L), "Medium" (M) and "High" (H) as shown in Figure 1b. The Overall Sustainability Performance is defined by using three fuzzy sets: "Weak" (W), "Acceptable" (A) and "Strong" (S) as shown in Figure 1c. In this study triangular and trapezoidal membership functions *μ(x)* are used for simplicity. A trapezoidal fuzzy set is used to represent the range of uncertainty for the Overall Sustainability Performance (OSP). Trapezoidal functions represent an increased uncertainty in the estimation of the OSP. The extent of the overlap between the OSP values is described by the membership functions in Figure 2c.

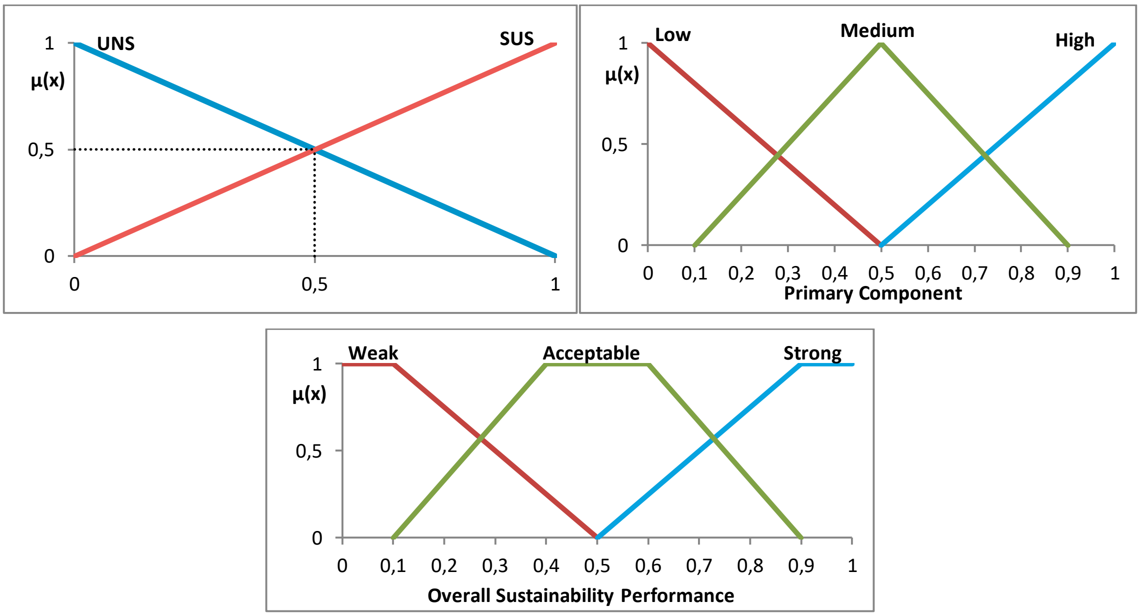

Figure 1. Fuzzy sets and corresponding membership functions μ(x), (a) membership function for the indicator, (b) Membership function for the primary component, (c) Membership function for the overall sustainability performance

3.2. Inference Step

This study uses a fuzzy system with multiple inputs, using the same linguistic values and a single output. The inference step is applied five times for inputs of the ENV, TECH, ENR, ECON and USER components and one time for inputs of the OSP, generating five plus one sustainability scores. The rules used in each inference step express in the case of the sustainability framework the dependence of a sustainability dimension on corresponding indicators. Rules of *"If-Then"* are used to generate an output from combined input values; the outputs from Level I are used as inputs at Level II. In this study the minimum inference method (i.e., *"min, If-part"*) is used to estimate the outputs of each level. The minimum operator is expressed by the term *"and"* in the set rules. Each rule is assigned a positive weight, which measures its relative importance on the implication process. For this study all rules are assigned the weight of one.

The rule base is obtained by assigning integer values to fuzzy sets (Pislaru and Trandabat 2012; Phillis and Davis 2008). The fuzzy sets for sustainability indicators at Level I are assigned integer values of 0 and 1, where 0 is assigned to the fuzzy set "UNS" and 1 to the fuzzy set "SUS". Similarly for primary sustainability components, the fuzzy sets are assigned integer values of 0, 1 and 2, where 0 is assigned to the fuzzy set "Low", 1 to "Medium" and 2 to "High". The estimated sum is assigned to a specific fuzzy set from "Low", "Medium" and "High" for the ENV, TECH, ENR, ECON and USER components and to the fuzzy sets "Weak", "Acceptable" and "Strong" for the Overall Sustainability Performance. Estimated sums of inputs for component and corresponding fuzzy sets are shown in Equation 1:

$$ENV = \begin{cases} L, & Sum = 0,1,2 \\ M, & Sum = 3,4 \\ H, & Sum = 5,6,7 \end{cases} \quad TECH = \begin{cases} L, & Sum = 0,1 \\ M, & Sum = 2 \\ H, & Sum = 3,4 \end{cases} \quad ENR = \begin{cases} L, & Sum = 0,1 \\ M, & Sum = 2 \\ H, & Sum = 3,4 \end{cases} \quad ECON = \begin{cases} L, & Sum = 0,1, \\ M, & Sum = 2,3 \\ H, & Sum = 4,5, \end{cases}$$

$$USER = \begin{cases} L, & Sum = 0,1,2 \\ M, & Sum = 3,4 \\ H, & Sum = 5,6 \end{cases} \quad OSP = \begin{cases} W, & Sum = 0,1,2,3 \\ A, & Sum = 4,5,6 \\ S, & Sum = 7,8,9,10 \end{cases} \tag{1}$$

Similarly, all sums for each rule are estimated and assigned to fuzzy sets "Low", "Medium" and "High" of the primary components at Level I. The number of rules per output is: ENV – 128 rules (7 input variables), TECH – 16 rules (4 inputs variables), ENR – 16 rules (4 inputs variables), ECON – 32 rules (5 inputs variables), USER – 64 rules (6 inputs variables). The final outcome at Level II is an evaluation of a vehicle's Overall Sustainability Performance as "Weak", "Acceptable" or "Strong". The rule base for estimating Overall Sustainability Performance is comprised of $3^5 = 243$ rules.

3.3. Aggregation

Fuzzy inputs were matched to their membership functions by using the "if-then" rules and then the outputs were aggregated. The fuzzy sets that represent the outcomes of each rule are combined into a single fuzzy set in the aggregation step. In this study the maximum aggregation method is used. Aggregation only occurs once for each output variable, just prior to the final step, defuzzification. For the outcomes of two rules represented by the produced fuzzy sets $\mu^1(x)$ and $\mu^2(x)$ the aggregated fuzzy set is represented by a membership curve (Pham and Castellani 2002):

$$\mu_i(x) = \max\left(\mu_i^1(x)\mu_i^2(x)\right) \tag{2}$$

3.4. Defuzzification

Defuzzification is the final step of the fuzzy method, in which a single crisp value is estimated. The input to the defuzzification step is a single fuzzy set produced in the aggregation step. The defuzzification technique of the center of gravity or centroid was used (equation 7). This technique takes the center of gravity of the membership function of the conclusion, which combines the membership function of each set rule. Where x^* is the defuzzified output, $\mu_i(x)$ is the aggregated membership function and x is the output variable.

$$x^* = \frac{\int \mu_i(x)\, x\, dx}{\int \mu_i(x)\, dx} \tag{3}$$

4. Sustainability Assessment Results

The fuzzy logic was applied for the sustainability assessment of five transportation vehicle types over five sustainability dimensions. The indicator values were weighted per passenger kilometer travelled (PKT). The Sustainability Index (SI) per dimension and the Overall Sustainability Performance index per vehicle type summarize the sustainability performance for the five vehicle types. Based on fuzzy logic based results, among the five vehicle types examined, the most sustainable vehicle is the hybrid bus with a score of 57.8 followed by the diesel bus with a score of 55.7. The overall sustainability performance for the EV, the HEV and the ICEV was 55.0, 51.1 and 48.2, respectively. Propulsion systems that depend exclusively or partially on electric drive did better than the traditional internal combustion engine technology when buses and passenger cars are compared separately.

The EV achieves the highest sustainability score among passenger cars due to its lower life cycle costs and environmental impact compared with the ICEV and the HEV. EV's score for Users was the lowest among passenger vehicles due to the assumption that 10% of the annual charging requirements obligate the user to stop to charge the vehicle, and due to the undeveloped network of charging stations compared to the gasoline dispensing network. Improvements in range performance and speed of charging will likely make EVs more competitive.

The EV has the highest economic sustainability index among passenger vehicles. The EV performs well for Economy due to its low maintenance and low fuel cost. Vehicle occupancy plays a critical role when estimating results on a passenger-kilometer basis; this is seen in the sustainability indices of DB and HDEB. The HDEB has the highest index for Environment with a significant difference from all other vehicles. Results for Environment show that utilization of alternative fuel technologies combined with policies that increase vehicle occupancy have the potential to improve passenger vehicle sustainability performance faster. For example, if occupancy was increased to two for all types of passenger vehicle, e.g., with extensive use of HOV-2 and HOT lanes, then the HEV would have the highest sustainability index of all vehicles, while DB would equal the ICEV's index. Emission intensity and sources differ for each vehicle type. For example, while ICEV produces more CO_2 emissions during its operation, EV produces more CO_2 during the production of its fuel. Policy formulation for treating impacts related to emissions should be based on the number and intensity of emission sources for each region. Without accounting for upstream emissions and energy requirements for alternative fuel vehicles, assessment of operation-only vehicle emissions and consumption create strong biases against ICEV, HEV and DB. Upstream emissions from, and energy requirements for vehicle fuel production, depend on the electricity mix used for every community. Therefore they are likely to vary significantly for different geographical areas.

Table 2. Sustainability assessment results and rankings per vehicle type using the fuzzy logic method

	Environment		**Technology**		**Energy**		**Economy**		**Users**		**Overall**	
	Ranking	**Fuzzy**	**Ranking**	**Fuzzy**	**Ranking**	**Fuzzy**	**Ranking**	**Fuzzy**	**Ranking**	**Fuzzy**	**Ranking**	**Fuzzy**
ICEV	5	45.6	5	36.9	5	34.2	5	43.7	2	29.6	5	48.2
HEV	4	54.6	3	42.2	4	48.3	4	49.5	1	40.8	4	51.1
EV	3	67.2	4	37.0	3	50.0	1	70.8	4	22.0	3	55.0
DB	2	67.6	2	65.4	2	62.5	3	50.0	3	23.6	2	55.7
HDEB	1	71.2	1	65.9	1	82.2	2	52.0	5	8.2	1	57.8

The results from the fuzzy method are not affected as much by the normalized values of 0 and 1. The set of indicators that is used for each vehicle to estimate the final score for one of the five sustainability dimensions in Table 2 does not activate all the predefined rules. Vehicle ranking changes in Table 2 tend to occur when several values of 0 or 1 exist in a set of vehicle indicators; such extreme values represent most or least sustainable performance relative to other vehicles. From a practitioner perspective, fuzzy logic indicators have the potential to be used in the assessment of transportation proposals, projects and alternative policies (e.g., parking, vehicle and fuel cost, vehicle occupancy, subsidy for alternative fuel vehicles). This method enables comparisons by mode type (e.g., private vehicle with technology X vs. bus), by broad class (e.g., motorized vs. non-motorized vehicles), by system (e.g., BRT vs. Light Rail), by corridor (e.g., HOT lanes vs. Mass Transit), and by area (comparisons of sections in the same city, or comparisons among cities or metro areas).

5. Monte Carlo Simulation

Monte Carlo Simulation (MCS) is a general procedure for risk and uncertainty analysis where random sampling is used to incorporate the inherent uncertainty or risk associated with the measurement of input variables (e.g., the measurement of the indicators for each of the sustainability dimension). MCS carries out a probabilistic analysis that treats the inputs of the sustainability index framework as ranges of values, it assigns a likelihood of occurrence to those values and allows for simultaneous variability among inputs, so that the outputs of probabilistic analysis are presented as a range with likelihood of occurrences (Bukowski and Wartenberg 1995, Chen et al. 2002).

In this research, the MCS is used to calculate the distribution percentiles of the sustainability indices for the five vehicle types by considering the uncertainty in the measurement of the indicators. The MCS is used herein to show that the values of the sustainability indicators should not be a deterministic number, but instead they could be represented as a range of values with a confidence interval and a probability distribution. For example, different vehicle models with similar vehicle type, which are made by various manufacturers can have slightly different measurement results and the measurements may have inherent observational errors.

In this study 5,000 iterations MCS were conducted to generate 5,000 data samples for each indicator and each vehicle type; the MCS process reached its convergent and stable status after 5,000 iterations. In practice, the sample size of MCS varies considerably for different projects or research subjects. The simulation results with nine deciles ranging from 5% to 95% show that:

- For Environment, the HDEB has the highest sustainability index compared with other vehicles. The EV and the DB indices appear to be similar in terms of Environmental sustainability. The ICEV has the lowest environmental sustainability index.
- For Technology, the HDEB and the DB have the highest sustainability indices compared with other vehicles and their difference is negligible. The EV and the HEV indices appear to be similar in terms of technology sustainability. The ICEV ranks last.
- For Energy, the HDEB sustainability index is slightly higher compared to the DB index, but both are significantly higher than all other vehicle types. The ICEV has the lowest Energy index; whereas the difference between the EV and the HEV index is negligible.
- For Economy, the EV has significantly the highest sustainability index and the ICEV has significantly the lowest sustainability index compared to other vehicle types. The HDEB and the DB indices appear to be similar.
- For Users, the HEV has the highest sustainability index, followed by the ICEV. The DB and the HDEB indices are found to be similar; while the EV has the lowest index.
- For the Overall Index, the HDEB is marginally superior to the DB. The HEV and the EV indices have no significant difference. Overall, the ICEV ranks as the least sustainable vehicle among the five vehicle types examined.

Table 3. Summary of vehicle types sustainability ranking

Sustainability Level	Environment SI	Technology SI	Energy SI	Economy SI	Users SI	Overall SI
High	HDEB	DB, HEDB	HDEB, DB	EV	HEV	HEDB
↓	DB, EV	HEV, EV	HEV, EV	HDEB, DB	ICEV	DB
	HEV	ICEV	ICEV	HEV	DB, HEDB	EV, HEV
Low	ICEV			ICEV	EV	ICEV

The results of the MCS on sustainability index and the rankings of all the vehicle types are summarized in Table 3. The findings in Tables 2 and 3 are consistent and support each other. As a conclusion, the MCS added value to this study by presenting the distribution characteristics of each sustainability index for the five vehicle classes, which added a layer of conservatism and statistical confidence in interpreting and comparing the advantages and disadvantages between vehicles types.

6. Conclusion

As new vehicle technologies and fuel types come with limited short and long-term data and introduce additional uncertainty in transportation planning, which must be accounted, this paper has sought to enhance decision making by combing fuzzy logic with the Monte Carlo simulation. The fuzzy logic method and the Monte Carlo Simulation were selected because sustainability assessment includes uncertain information, imprecise data and interrelations between sustainability dimensions. The MCS used 5,000 re-sampling iteration to integrate assumed probability distributions of the sustainability assessment framework inputs (i.e., the raw indicators) and produce the output distribution statistics of the dimensions for each vehicle type.

Vehicle types examined included light duty vehicles powered by an internal combustion engine, a hybrid electric power plant, an electric drive, as well as two heavy duty transit vehicles, a diesel bus and a hybrid diesel electric bus. The sustainability assessment method can readily accommodate electric buses, CNG/LNG-powered vehicles and motorcycles. Based on the fuzzy logic method presented herein, the most sustainable vehicle is the hybrid diesel electric bus. The electric car was found to have the best sustainability performance among light duty vehicles. Propulsion systems that depend exclusively or partially on electric drive did better than the traditional internal combustion engine technology when bus and passenger cars are compared separately.

In addition to explicitly considering various propulsion technologies and fuels, the proposed sustainability assessment method enhances the traditional transportation planning process in three directions by including: (i) Vague and uncertain values of features of new vehicle technologies and fuels; (ii) Fuzzy interrelations between sustainability dimensions; and, (iii) Uncertainty due to the subjective judgment and preferences of decision makers.

While the fuzzy method incorporated uncertainty in the assessment of the vehicle final rankings, it did not convey the uncertainty of the output. This shortcoming was addressed by implementing the Monte Carlo method, where a range of possible outputs between 5% and 95% percentile is estimated in response to uncertainties in input data (i.e., the uncertainty in the measurement of indicators for the five primary components) generated for the sustainability assessment of transportation vehicles. Although, the fuzzy logic and MCS are different ways of expressing uncertainty, the fuzzy method supplemented by MCS improved the sustainability ranking of transportation vehicles by conveying uncertainty in the output. Both methods produced comparable results. The fuzzy-and-MCS method provided a robust approach for assessing the sustainability of transportation vehicles and for supporting decision making in transportation planning.

References

APTA – American Public Transportation Association, 2009. Public Transportation fact Book, 60th Edition.

Bukowski, Korn L. and Wartenberg D., 1995. Correlated Inputs in Quantitative Risk Assessment: The Effects of Distributional Shape, Risk Analysis, 15(2), 215-219.

Chen, A., Yang, H., Lo, H. K., and Tang, W. H., 2002. Capacity Reliability of a Road Network: an Assessment Methodology and Numerical Results, Transportation Research Part B 36, pp. 225-252.

CTR – Center for Transportation Research, 2006. Operating Manual for GREET - Version 1.7. Argonne National Laboratory.

CTR – Center for Transportation Research, 2005. Development and Applications of GREET 2.7. The Transportation Vehicle-Cycle Model. Energy Systems Division, Argonne National Laboratory.

CTR – Center for Transportation Research, 1998. Total Energy Cycle Assessment of Electric and Conventional Vehicles: An Energy and Environmental Analysis, Volume 1." Argonne National Laboratory.

EPA – Environmental Protection Agency, 2003. User's Guide to MOBILE6.1 and MOBILE6.2. U.S.

Hardy, T.L, 1995. "Multi-Objective Decision Making under Uncertainty: Fuzzy Logic Methods". NASA Technical Memorandum, Computing in Aerospace Meeting, National Aeronautics and Space Administration Lewis Research Center, Ohio, USA..

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

Mitropoulos, L., Prevedouros, P. 2013. Assessment of Sustainability for Transportation Vehicles. Transportation Research Record: Journal of the Transportation Research Board, 2344, 88–97.

Phillis, Y.A. Davis, B.J., 2008. Assessment of Corporate Sustainability via Fuzzy logic. J Intell Robot Sust, Vol 55,3-20.

Pislaru, M., Trandabat, A.F., 2012. Fuzzy Based Environmental System Approach for Impact aAsessment – Case studies. World Academy of Science, Engineering and Technology, Vol 67, 1136-1141.

Pham, D.T., Castellani, M., 2002. Action Aggregation and Defuzzification in Mamdani-type Fuzzy Systems". Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, 216, 747-759.

Pislaru, M., Trandabat A.F., Curteanu, S., 2012. Fuzzy Environmental Assessment of Urban Areas Sustainability. 2nd International Conference on Environment and Industrial Innovation, Vol 35.

Rossi, R., Gastaldi, M., Gecchele, G., 2013. Comparison of a Fuzzy-based and AHP Methods in Sustainability Evaluation: A Case of Traffic Pollution-Reducing Policies. European Transport Research, 5, 11-26.

TCRP – Transit Cooperative Research Program, 2003. Bus Rapid Transit, Volume 1: Case Studies in Bus Rapid Transit. Transportation Research Board of the National Academies, Report 90.

TTI – Texas Transportation Institute. (2009). Urban mobility report. http://tti.tamu.edu/. Accessed June, 2015