LCA Case Studies

Using Monte Carlo Simulation in Life Cycle Assessment for Electric and Internal Combustion Vehicles

David L. McCleese and Peter T. LaPuma¹

Air Force Institute of Technology, Wright-Patterson Air Force Base, OH 45433, USA

¹Corresponding author (peter.lapuma@afit.edu)

DOI: http://dx.doi.org/10.1065/lca2002.02.073

Abstract

1 Background. The U.S. Government has encouraged shifting from internal combustion engine vehicles (ICEVs) to alternatively fueled vehicles such as electric vehicles (EVs) for three primary reasons: reducing oil dependence, reducing greenhouse gas emissions, and reducing Clean Air Act criteria pollutant emissions. In comparing these vehicles, there is uncertainty and variability in emission factors and performance variables, which cause wide variation in reported outputs.

2 Objectives. A model was developed to demonstrate the use of Monte Carlo simulation to predict life cycle emissions and energy consumption differences between the ICEV versus the EV on a per kilometer (km) traveled basis. Three EV technologies are considered: lead-acid, nickel-cadmium, and nickel metal hydride batteries.

3 Methods. Variables were identified to build life cycle inventories between the EVs and ICEV. Distributions were selected for each of the variables and input to Monte Carlo Simulation software called Crystal Ball 2000[®].

4 Results and Discussion. All three EV options reduce U.S. oil dependence by shifting to domestic coal. The life cycle energy consumption per kilometer (km) driven for the EVs is comparable to the ICEV; however, there is wide variation in predicted energy values. The model predicts that all three EV technologies will likely increase oxides of sulfur and nitrogen as well as particulate matter emissions on a per km driven basis. The model shows a high probability that volatile organic compounds and carbon monoxide emissions are reduced with the use of EVs. Lead emissions are also predicted to increase for lead-acid battery EVs. The EV will not reduce greenhouse gas emissions substantially and may even increase them based on the current U.S. reliance on coal for electricity generation. The EV may benefit public health by relocating air pollutants from urban centers, where traffic is concentrated, to rural areas where electricity generation and mining generally occur. The use of Monte Carlo simulation in life cycle analysis is demonstrated to be an effective tool to provide further insight on the likelihood of emission outputs and energy consumption.

Keywords: Battery; Clean Air Act Amendments (CAAA); criteria pollutants; electric vehicle; energy; life cycle assessment (LCA); life cycle inventory (LCI); lifecycle; Monte Carlo, probabilistic

1 Background

Exhaust emissions from internal combustion engine vehicles (ICEVs) contribute to air pollution resulting in deleterious impacts to the environment and human health. Additionally, they rely on refined crude oil making the U.S. dependent on foreign oil imports, which now account for the majority of total U.S. oil consumption. Net imports accounted for 53% of U.S. consumption in 2000 [1]. In response to these issues, the U.S. Federal Government has passed legislation (Energy Policy Act of 1992) and issued several Executive Orders [2–4] with the following goals:

- 1. Reduce foreign oil dependence
- 2. Reduce carbon dioxide (CO_2) emissions
- 3. Reduce the six Clean Air Act criteria pollutant air emissions

One approach to accomplishing these goals is to encourage the use of alternatively fueled vehicles that would reduce air emissions and consume less oil. One type of alternatively fueled vehicle is the grid-dependent electric vehicle (EV). During use, the electrical power grid provides the energy needed to recharge the grid-dependent EV. Many renewable energy sources such as wind, solar, hydroelectric, geothermal power and nuclear power convert other forms of energy to electricity. While electricity can be used to produce other energy sources (i.e. hydrogen), the most direct use of electricity in the transportation sector is to recharge EV batteries. There are several drawbacks with the use of EVs, such as limited range and lack of infrastructure. Other alternatively fueled vehicle technologies, such as fuel cell or hybrid engine systems, may enjoy broader acceptance but all powered vehicles will require some form of stored energy and EVs may have practical applications for many short-range driving needs. Many variables necessary to perform a life cycle inventory (LCI) to compare EVs and ICEVs have a great deal of uncertainty and variability, which results in a wide range of reported outputs using traditional LCI techniques.

2 Objectives

The primary intent of this research is to demonstrate the use of Monte Carlo simulation within a LCI framework. This research will compare the differences in life cycle criteria pollutant emissions, greenhouse gas emissions and energy usage between ICEVs and three EV technologies to quantify the impact of EV use with respect to achieving the aforementioned goals. The three EV types selected for evaluation in this research are the lead-acid battery EV, the nickel-cadmium (Ni-Cd) battery EV, and the nickel metal hydride (NiMH) battery EV, which are currently the most available forms of rechargeable battery technologies [5].

3 Methods

LCI quantifies the energy and materials used and wastes released to the environment during all phases of the life of a product. Product life cycle is divided into raw material extraction, material preparation, manufacture, use, and final disposal [6]. LCI is comprehensive because all phases of a product life cycle are considered. Often, vehicle emission estimates focus on the use phase (i.e. driving) and neglect to consider the energy use and emissions during the other life cycle phases (i.e. raw material extraction). For example, replacing steel automobile components with lighter aluminum lowers vehicle weight and reduces energy during the vehicle use phase. However, primary aluminum production is more energy intensive than primary steel production. Though recycled aluminum would reduce energy consumed for aluminum to some degree, the additional energy needed for raw materials could offset the reduction in energy during the vehicle use phase [7]. When the life cycle perspective is applied, all activities necessary to propel a vehicle a given distance are represented. The life cycle perspective is a closer reflection of the broad environmental impact of a vehicle design.

LCI is appropriate for complex comparisons. ICEVs require gasoline which uses energy in drilling, extraction, transport, refining, etc. and EVs require electricity, which is predominantly fueled by coal in the U.S. An Energy Information Administration (EIA) report indicates that natural gas will be the fastest growing fuel source in electricity production but coal is still expected to produce 44 percent of the U.S. electricity in 2020 (from 51% in 1999) [1]. One reason that coal is likely to remain a major source for electricity in the U.S. is because the U.S. has the worlds largest supply of ultimately recoverable coal lasting over 200 years [1]. The energy mix used to produce electricity may shift in the future, but like ICEVs, EVs consume energy and result in emissions emitting pollutants and greenhouse gases, though the magnitude and location of the emissions may change with EVs versus ICEVs.

3.1 Monte Carlo Simulation

Most emission models in widespread use, such as EPA's mobile source emissions model, MOBILE, rely on deterministic methods to characterize emissions [8]. In other words, a single value is assigned to each input variable and a single value is computed for each output. The deterministic method produces an output that does not address the variability or uncertainty inherent in each of the input variables. These deterministic estimates fail to place point estimates in the context of the uncertainty in which they were developed [9]. One way of accounting for the variability and uncertainty of emissions and energy inputs for the EV and the ICEV is to use probabilistic methods such as Monte Carlo simulation. Monte Carlo simulation is a technique of simulating real world behavior with variable distributions instead of point values [10]. A large degree of natural variability is inherent in vehicle emissions due to factors like engine design, maintenance and vehicle age. For example, when an ICEV ages, its emission control systems, primarily the catalytic converter, become less effective causing some ICEVs to become 'high emitters'. A study by Bishop et al. concluded that the dirtiest 10% of vehicles at a Phoenix exit ramp were responsible for 78%, 79% and 49% of the carbon monoxide (CO), hydrocarbon (HC) and oxides of nitrogen (NOx) emissions [11], respectively. A study of California vehicles reports that 7% of the automobiles account for 50% of the CO and hydrocarbons emitted [12]. By using Monte Carlo to specify a distribution for ICEV emissions, a range of probable estimates to include the high emitters will provide a better representation of reality.

There is also a great deal of uncertainty in vehicle emission factors and battery design parameters. The literature has many contradictory emission factors, and references to 'unpublished information' [7]. For example, the EPA AP-42 database is the most widely used air emission factor database available. However, it is widely recognized that some of these data are of 'average' quality [13]. Uncertainty in emission factors is further compounded because industries prefer discretion with respect to the pollution they emit [14]. Also, gathering data to develop accurate emission factors is often expensive and time consuming, sometimes taking years to compile [15]. The advantage with Monte Carlo simulation is that it allows the modeler to estimate the uncertainty in each input variable and predict the impact of that variable on the outputs. The Monte Carlo method provides the decision maker with a range of potential outcomes along with the predicted chance of their occurrence.[16]

Input variables such as emission factors are often the cause of controversy because there are many vested interests at stake and uncertainty in the values. An article by Lave et al.[5] concluded that lead-acid EVs would emit 60 times more lead per km than a comparable car burning leaded gasoline. This article sparked a series of letters to the editor claiming that the lead emission factors of 4% for virgin lead production and 2% for recycled lead production were too high [17]. There will always be some controversy over the most appropriate input to use but Monte Carlo simulation provides a tool to estimate the uncertainty based on a broad range of viewpoints. Then, through sensitivity analysis, if a variable is shown to have little or no impact on the output of interest, further debate over the 'most accurate' value becomes moot.

The software used in this study is Crystal Ball 2000 from Decisioneering Incorporated which is designed to work with Microsoft Excel [10]. The software randomly selects a value within the distributions assigned for each input variable and then computes the outputs. This process is repeated and the collective outputs from each iteration combine to form a probability distribution function (PDF). This PDF expresses both central tendency and the variability in the output variable arising from the variation in the input variables.

3.2 General assumptions

This research focused on the difference between the EV and the ICEV. In order to compare similar vehicles, a mid-size sedan as presented by Sullivan et al. is assumed [18]. The emissions and energy consumed from common features such as tires, glass, and paint will not be evaluated. Resource extraction, material preparation, manufacture and use phases of a vehicle will be evaluated but the disposal phase of the vehicle will be ignored because there are many possible disposal options. The disposal phase is anticipated to have relatively few air emissions and little energy consumption, although the inappropriate disposal of lead-acid batteries could release substantial amounts of lead, which can be transported to water or soil [19]. Vehicle assembly is also ignored in this study. Assembly is required for both types of vehicles and even though the EV may require less assembly energy because it is less complicated, the differences in assembly are anticipated to be relatively minor.

3.3 Raw material assumptions

In order to compute the energy and emissions required to manufacture and maintain the vehicle, the mass of each raw material in the EV relative to the ICEV is determined. Several factors influence manufacturers' material selection including material weight, cost, manufacturing techniques, and government requirements [20]. ICEV material composition is relatively well known as the ICEV vehicle design has been optimized over many years [18]. Current recycling rates were considered for each material when developing emission factor distributions. For example, it was assumed that 70–90% of wrought aluminum in a vehicle is from recycled aluminum, which is less energy intensive to process per unit mass of aluminum [7]. EV battery mass for initial manufacture and replacement is dependent on vehicle performance assumptions, including range and battery energy density, which differs for each of the three battery technologies. To determine battery composition, the Monte Carlo simulation model determines the total battery mass based on selected values for vehicle range and battery energy density. Once these variables are determined, the battery mass required to achieve the selected range is computed in the model using eq 1.

Battery mass (kg) =
$$\frac{\text{Energy requirement } (kWh/km)}{\text{Energy density } (kWh/kg)} * \text{Vehicle Range (km)} (1)$$

Once the battery mass is determined, the material composition of the batteries is used to calculate the mass of each material. The emission factors for each material are then multiplied by the material mass as shown in eq 2.

Material (kg) * Emission Factor (g/kg material) = Emission (g) (2)

The energy required for each material is computed in a similar manner. The energy inputs and emissions from each material are then summed to compute the energy and emissions per battery. The number of battery replacements needed over the life of the vehicle is determined based on vehicle life and battery life. This process is repeated using a new set of randomly selected variables for each iteration of the Monte Carlo simulation.

3.4 Vehicle use phase

In general, the EVs will require replacement batteries and electricity while the ICEV will require engine part replacements, oil and gasoline. For EVs, the energy and emissions needed to produce a given quantity of electricity in the U.S. along with transmission line losses and battery charging efficiencies are all considered. The emissions and energy used to produce electricity is based on a life cycle inventory done by the EPA on the entire U.S. electrical energy grid for 1997 [13]. Some adjustments were made to the assigned distributions for this model to account for future emission trends. For the ICEV, the energy and emissions to make gasoline available such as crude oil production, oil refining, shipment and distribution are considered in the model as well. Several emission factors were calculated from the Economic Input-Output Life Cycle Assessment (EIO-LCA) model developed at Carnegie Mellon University [21].

The distance a vehicle travels in its lifetime is used as the baseline unit of activity because the primary role of a midsize sedan is to move people (or perhaps cargo) a certain distance. Empirical evidence demonstrates that a younger vehicle is driven more per year than an older one. Erlbaum's study finds that, on average, a one year old vehicle is driven nearly 13,000 miles while a 12 year old vehicle is driven only 8,000 miles [22]. Another study was used to determine the distribution of the vehicle-scrapping rate or vehicle age at disposal [23]. The Monte Carlo simulation selects the age of the vehicle and then sums all the annual miles driven up to the vehicle age to arrive at the total life cycle driving distance PDF. All vehicles were assumed to survive until the end of year 1 and the maximum life was truncated at 34 years.

Because older vehicles tend to become high emitters, [12] a gamma distribution was assigned to some of the ICEV in-use emissions as recommended by Zhang et al [24]. The parameters of the gamma distributions assumed in the model were developed from real-world samples of over 20,000 vehicles reported by Bishop [25].

4 Results and Discussion

Outputs are presented as box-and-whiskers plots that depict the PDF of the output variables. For example, Fig. 1 represents the difference in energy consumption for each of the three EV technologies referenced to the ICEV. Note that the box and whiskers are plotted with respect to a life cycle ICEV baseline value. Because elements common to all vehicles were excluded from this study, this Monte Carlo simulation computes the life cycle difference between each EV and the ICEV values from the model.



Fig. 1: EV life cycle energy difference with ICEV baseline

To provide a sense of scale, a deterministic study published by Sullivan et.al. was used as the ICEV baseline, which is the total life cycle emissions and energy used for an ICEV assuming a 120,000 mile (192,000 km) vehicle lifetime [15]. The box and whiskers therefore can be viewed as representing the EV against a baseline representing the ICEV. The dash within each box is the 50th percentile difference. The ends of the box represent the 25th and 75th percentile. The endpoints are the 2.5th and 97.5th percentile differences. The generic equation for the data represented in the box and whisker plots is shown in eq 3.

$$Iteration_{i} = ICEV_{Sullivan} + (EV_{Sim} - ICEV_{Sim})_{i}$$
(3)

Where:

Iteration_i = one model iteration to compute box and whiskers ICEV_{Sullivan} = baseline point value for ICEV reported by Sullivan et al. [15] EV_{Sim} = value for one iteration of the Monte Carlo simulation for EV

 $ICEV_{Sim}$ = value for one iteration of the Monte Carlo simulation for ICEV

Fig. 1 shows the median life cycle energy consumed per km traveled was generally lower for all EV technologies than for the ICEV. The median value for the lead-acid battery EV is just over 4,200 kJ/km while the baseline ICEV is just over 5,070 kJ/km. However, note that the upper edge of the box, the 75th percentile, is roughly equal to the ICEV baseline. This shows that with all the input distributions, 25% of the 10,000 randomly simulated combinations resulted in a higher energy demand per km for the lead-acid battery EV than for the ICEV. This demonstrates a strength of Monte Carlo analysis. If someone reported that the lead-acid battery EV consumes more energy per km than an ICEV, there is a 25% chance that they are correct according to this model. However, Fig. 1 shows that there is a greater chance, 75%, that the lead-acid battery EV will use less energy per km than the ICEV. Also, 95% of the possible outcomes for the lead-acid battery EV have a range from about 2,000 kJ/km (2.5th%) to 7,000 kJ/km (97.5th%), a 5,000 kJ/km range. This wide range of possible energy consumption values demonstrates the inherent uncertainty in the LCI variables.

4.1 Life cycle energy

An interesting output variable to examine is the life cycle energy by source for the ICEV versus the EVs. Fig. 2 illustrates that all three EV technologies would accomplish the goal of reducing oil imports (though there is a substantial increase in the use of coal due to increased electricity needs). This assessment assumes the current U.S. energy inputs for electricity production. An increase in the use of renewable energy or natural gas sources to make electricity would reduce the demand for coal-derived electricity. However, ac-



Fig. 2: Vehicle lifecycle energy differences by source



Fig. 3:Median energy consumption by life cycle phase

cording to a recent government report, 'renewables are projected to make up a smaller share of U.S. electricity generation, declining from 10.5 percent in 1999 to 8.5 percent in 2020'[1]. Renewable energy sources also need to be evaluated using a life cycle approach to fully evaluate their environmental impacts. It takes energy to acquire the materials to manufacture solar cells or wind mills. Note that this research is focused on the differences between the ICEV versus the three EVs so Fig. 2 is not the total consumption of energy consumed per km but the difference. The missing portion of life cycle energy consumed is likely to be similar in quantity and composition across all four vehicle types.

Fig. 3, shows the energy consumption differences broken out by life cycle phase. The median values from the Monte Carlo simulation were used to construct Fig. 3. The maintenance energy for the lead-acid and Ni-Cd EVs are higher than the ICEV due the need for battery replacements.

4.2 Air emissions

Fig. 4 shows the expected CO_2 and CO_2 equivalents (CO_2E – other greenhouse gases converted to CO_2 equivalents based on global warming potential) emissions for the EVs with respect to the ICEV baseline. For lead-acid battery EV, the majority of potential CO_2E emissions is greater than ICEV and



Fig. 4: EV life cycle CO_2 equivalent (CO_2E) emissions with ICEV baseline. (Values do not include common elements such as tires, glass or paint)

the opposite is true for NiMH battery EVs. However, the range of possibilities is so wide that CO_2E emissions could either increase or decrease. In short, EVs do not have a high probability of reducing greenhouse gas emissions and their use may even increase CO_2E . This may seem counterintuitive because Fig. 1 shows a slight decrease in total energy use per distance traveled with EV use. This disparity is partly explained by the fact that coal emits more CO_2 per unit energy generated than gasoline. Coal has a wide range of chemical compositions but generally contains less hydrogen per unit mass than gasoline and emits approximately 24g of carbon per MJ energy in contrast to gasoline, which emits approximately 19g of carbon per MJ energy [25].

An important point to be made with regard to greenhouse gas emissions is that even though the EVs themselves do not emit CO_2E , the life cycle perspective illustrates that the activity of driving an EV does emit a comparable amount of CO_2E per unit distance traveled. Because greenhouse gas emissions are a global concern, it is irrelevant which part of the life cycle emits the CO_2E . The increased use of coal, the energy losses in the conversion of coal to electricity, the losses in the power transmission system, the battery charger and battery efficiencies along with the EV energy requirements all contribute to CO_2E emissions from an EV.

Fig. 5 illustrates the EV emissions of SO₂ and CO in relation to the ICEV SO₂ baseline emission of 0.69 g/km and the ICEV CO baseline emission of 9.5 g/km [15]. Fig. 5 indicates that it is virtually certain that SO₂ emissions per km will increase with any EV compared to the ICEV. The sulfur dioxide (SO_2) emission from electricity production of 3.64 g/KWh was based on a life cycle inventory done by the EPA on the U.S. electrical energy grid [13]. However, this life cycle inventory on the electric grid pre-dates the Phase II SO₂ reductions required by the 1990 Clean Air Act Amendments (CAAA) for all coal-fired power plants in the year 2000. There is also some debate over further reducing SO_2 emissions to 80% below 1997 levels [26]. Therefore, a uniform distribution from 2.2 to 4.0 g/KWh (-40% to + 10%) is assumed for SO₂ emissions. A 40% reduction in SO₂ emissions per KWh of electricity reflects an 80% reduction in sulfur emissions from coal consumption because coal com-



Fig. 5: EV life cycle sulfur dioxide (SO_2) and carbon monoxide (CO) with ICEV baseline

prises roughly half the electricity production in the U.S. For CO, the very long tails that extend into negative values is caused by the fact that a gamma distribution was assumed for the ICEV CO emission factor to account for the probability of a high emitting ICEV. The baseline ICEV value was deterministically calculated and does not assume an emission factor for high emitters. When an ICEV has a very high CO emission, the difference between the $EV_{gCO/km}$ – ICEV_{gCO/km} is a large negative value. The 2.5th percentile difference is -31.5 gCO/km but the baseline ICEV CO emission is only 9.5 gCO/km resulting in the unrealistic prediction of the EV emitting -22 gCO/km. This aberration is caused by the comparison with a deterministic estimate that does not allow for high emitters. This helps illustrate how deterministic methods can mask important information.

In Fig. 6, NO_x emissions are generally higher for the EVs (median ~1.8 g/km) versus the ICEV at 1.3 g/km. The EPA life cycle inventory of the U.S. electric grid concludes that 1.7 g of NOx are emitted per KWh of electricity produced in the U.S. [13]. However, there is also some debate to reduce the NOx emissions from coal-fired power plants by up to 75% of 1997 levels [26]. Therefore, a uniform distribution from 1.1 to 1.9 (-35% to +10%) is assumed for NOx emissions. As mentioned before, a 35% reduction (1.1 g/KWh) in NOx emissions per KWh of electricity reflects a 70% reduction in sulfur emissions from coal consumption because coal comprises roughly half the electricity production in the U.S. As seen with CO emissions, the longer lower tails on the NOx and the VOCs are also because a few ICEVs can become high NO_x or VOC emitters. PM_{10} shown in Fig. 6 are almost certain to increase with the use of EVs. The increased emissions are largely due to coal combustion.

The model also demonstrates that the lead-acid battery EV will increase lead emissions but the Ni-Cd and NiMH battery

EVs will reduce lead emissions slightly because the lead-acid starter battery in the ICEV is eliminated. The ICEV life cycle emission for lead is only 0.0005 g/km [15]. The model predicts the median increase in lead emissions for lead-acid battery EVs is 0.15 g/km with a 2.5th and 97.5th percentiles at 0.01 and 0.56 g/km. There is a wide range because of the uncertainty in the appropriate emission factor to apply for lead manufacturing [19]. A wide uniform distribution for lead emissions was assumed, 0.01 to 20 g/kg of lead produced.

Because the 2.5th percentile for lead emissions is positive, there is a 97.5% chance that lead emissions will increase. This model does not characterize the lead emission by media (air, water, soil, etc.). This distinction was omitted because lead is persistent in the environment and lead emission in any media is assumed to be deleterious. The fate and transport of lead in the environment is complex. Even the lead emissions from leaded fuel went directly into the atmosphere before depositing onto soils or surface water. One distinction, however, is that lead emissions for EVs are less likely to occur in populated urban centers because lead mining and smelting tend to occur in less populated areas. The lead emissions from leaded gasoline were concentrated near urban centers where traffic was heavy. The Monte Carlo simulation also does not account for improper battery disposal. Although the expense of a lead-acid battery will encourage recycling, some improper disposal of lead-acid batteries is inevitable. It should also be noted that even though the majority of lead-acid batteries would be recycled, the initial start-up demand for virgin lead will be high if leadacid battery EVs are used on a large scale. It is also important to point out that even though the other EV types do not increase lead emissions, the Ni-Cd battery EV will require comparable amounts of nickel and cadmium and the NiMH battery EV will require nickel and some other selected metal.



Fig. 6: EV life cycle emissions for NO_x, VOCs and PM₁₀ with ICEV baseline

A sensitivity analysis demonstrates that the EV energy requirement in Wh/km contributes the greatest degree of variability for total energy consumed, CO_2E and SO_2 emissions for all three EVs. The EV energy requirement is dominant for several other emissions as well. The EV energy requirement is equivalent to ICEV gas mileage and has a wide triangular distribution with a minimum, peak and maximum value of 150, 377 and 528 Wh/km, respectively [5,18,27,28].

This research demonstrates that Monte Carlo simulation used within a life cycle framework can enhance understanding of complex comparisons like EV versus ICEV. A great deal of effort is spent debating the 'most appropriate' value to select for a given input variable to include how long a vehicle or battery will last or what the air emission factor should be. All these variables have uncertainty and variability associated with them. Monte Carlo simulation is a tool well suited to understand the magnitude of the uncertainties and variability that are difficult to observe using deterministic methods.

References

- U.S. Department of Energy, Energy Information Administration (2001): Annual Energy Outlook 2001 With Projections to 2020; U.S. Government Printing Office, Washington DC DOE/ EIA-0383. Available at <u>http://www.eia.doe.gov/oiaf/aeo</u>
- [2] Clinton WJ (1993): Executive Order 12844: Federal Use of Alternative Fueled Vehicles. 58 Federal Register 21885
- [3] Clinton WJ (1996): Executive Order 13031: Federal Alternative Fueled Vehicle Leadership. 61 Federal Register 66529
- [4] Clinton WJ (2000): Executive Order 13149: Greening the Government Through Federal Fleet and Transportation Efficiency. 65 Federal Register 24607
- [5] Lave LB, Hendrickson CT, McMichael FC (1995): Environmental Implications of Electric Cars. Science 268, 993–995
- [6] Gloria T, Saad T, Breville M, O'Connell M (1995): Life Cycle Assessment: A Survey of Current Implementation. Total Quality Environmental Management 33–49
- [7] Stodlsky F, Vyas A, Cuenca R, Gaines L (1995): Life Cycle Energy Savings Potential from Aluminum-Intensive Vehicles. In Total Life Cycle Conference & Exposition Transportation Technology, Vienna, Austria
- [8] U.S. Department of Transportation (1994): Evaluation of the MOBILE Vehicle Emissions Model. U.S. Government Printing Office, Washington DC, 600–572. Available at <u>http://</u> ntl.bts.gov/DOCS/mob.html
- [9] Finkel AM (1995): Toward Less Misleading Comparisons of Uncertain Risks: The Example of Aflatoxin and Alar. Environmental Health Perspectives 130, 376-385
- [10] Decisioneering Incorporated (2000): Crystal Ball 2000 Users Manual
- [11] Bishop GA, Pokharel SS, Stedman DH (2000): On-Road Remote Sensing of Automobile Emissions in the Phoenix Area: Year 1. Coordinated Research Council; Alpharetta, Georgia Available at <u>http://www.feat.biochem.du.edu/assets/databases/ Ariz/Phoenix/Phoenix year 1.pdf</u>
- [12] Beaton S P, Bishop GA, Zhang Y, Ashbaugh LL, Lawson DR, Stedman DH (1995): On-Road Vehicle Emissions: Regulations, Costs, and Benefits. Science 268, 991–992

- [13] Socolof ML, Overly JG, Kincaid LE, Singh D, Hart KM (2000): Preliminary Life Cycle Assessment Results for the Design for the Environment Computer Display Project. In 2000 IEEE International Symposium on Electronics and the Environment, San Francisco, California Available at <u>http://</u>
- [14] MacLean HL, Lave LB (1998): A Life Cycle Model of an Automobile. Environmental Science & Technology 3, 322–330

ieeexplore.ieee.org/iel5/6935/18632/00857664.pdf

- [15] Sullivan JL, Williams RL, Yester S, Cobas-Flores E, Chubbs ST, Hentges SG, Pomper SD (1998): Life Cycle Inventory of a Generic U.S. Family Sedan Overview of Results USCAR AMP Project. Society of Automotive Engineers, Report No 982160
- [16] Finley B, Paustenbach DJ (1994): The Benefits of Probabilistic Exposure Assessment: Three Case Studies Involving Contaminated Air, Water, and Soil. Risk Analysis 14, 55–73
- [17] Letters to the Editor (1995): Science 269, 741-743
- [18] Sullivan JL, Hu J (1995): Life Cycle Energy Analysis for Automobiles. Society of Automotive Engineers Report No 951829
- [19] Lave LB, Russell AG, Hendrickson CT, McMichael FC (1995): Battery Powered Vehicles: Ozone Reduction versus Lead Discharges. Environmental Science and Technology 30, 402–407
- [20] Kandelaars P, van Dam JD (1998): An Analysis of Variables Influencing the Material Composition of Automobiles. Resources, Conservation and Recycling 24, 223–333
- [21] Green Design Initiative (2000): Economic Input-Output Life Cycle Assessment Model, Carnegie Mellon University Available at <u>http://www.eiolca.net</u>
- [22] Erlbaum NS (1999): Improving Air Quality Models in New York State: Utility of the 1995 Nationwide Personal Transportation Survey. New York State Department of Transportation
- [23] Miaou SP (1995): Factors Associated with Aggregated Car Vehicle-scraping Rate in the United States: 1966–1992. Oak Ridge National Laboratory, Oak Ridge TN, USA
- [24] Zhang Y, Bishop GA, Stedman DH (1994) Automobile Emissions Are Statistically Gamma-Distributed, Environmental Science and Technology 28, 1370–1391
- [25] Marland G.(1983): Carbon Dioxide Emission Rates for Conventional and Synthetic Fuels. Energy 8, 981–992
- [26] U.S. Department of Energy, Energy Information Administration (2001): Reducing Emissions of Sulfur Dioxide, Nitrogen Oxides and Mercury from Electric Power Plants; U.S. Government Printing Office, Washington DC SR/OIAF/2001-04 Available at <u>http://www.eia.doe.gov/oiaf/servicerpt/mepp/pdf/</u> <u>sroiaf(2001)04.pdf</u>
- [27] Wang Q, DeLuchi MA (1992): Impacts of Electric Vehicles on Primary Energy Consumption and Petroleum Displacement. Energy 17, 351-366
- [28] Alternative Fuels Vehicle Data Center (2001): Model Year 2001 Vehicle Chart. U.S. Department of Energy, Office of Transportation Technologies Available at <u>http://www.afdc.doe.gov/pdfs/wModel Year2001AFVs.pdf</u>

The views expressed in this article are those of the authors and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the US Government.

Received: October 10th, 2001 Accepted: January 23rd, 2002 OnlineFirst: February 5th, 2002

Int J LCA 7 (4) 2002