# *GREEN TRANSIT SCHEDULER*: A METHODOLOGY FOR JOINTLY OPTIMIZING COST, SERVICE, AND ENVIRONMENTAL PERFORMANCE IN DEMAND-RESPONSIVE TRANSIT SCHEDULING

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## ABSTRACT

Many types of transportation systems, for example, public transit and commercial freight hauling and package delivery, may be categorized as being fleet operations. The environmental impacts of fleet operations such as these are affected by factors including the initial choice and selection of vehicles (types) comprising the fleet, vehicle age and maintenance, and the modal conditions under which the vehicles are operated including. And, the environmental impacts are even more significant when examined on a life-cycle basis. When examined on this basis, it is clear that "cleaner" fuels, alone, do not provide an environmental panacea or eliminate all of the environmental impacts of transportation. Moreover, many of the life-cycle impacts can be directly or indirectly attributed to vehicle operation. Controllable life-cycle impacts may also be affected by vehicle routing and scheduling decisions, in particular, in the case of a heterogeneous fleet. And, these other controllable environmental impacts of transportation systems and operation must also be considered if the overall impacts are truly to be minimized.

There has been little prior work that has considered environmental impacts in fleet vehicle routing and scheduling optimization, in particular, where the impacts were assessed systematically utilizing life-cycle impact assessment (LCIA) methodologies such as those described by SETAC (1993, 1991) and in current ISO standards (ISO 14040). In this report, we present a methodology and algorithm for the joint optimization of cost, service, and life-cycle environmental consequences in vehicle routing and scheduling, which we develop for a demand-responsive (paratransit or "dial-a-ride") transit system. Importantly, as a prerequisite to accomplishing this, we develop a decision-theoretic-based model for combining the results of multiple, current LCIA methods, as suggested by Bare, et al. (2000). And, we use the results of this model as the basis for specifying necessary weighting constants in the vehicle routing and scheduling objective function. We demonstrate through simulation that, as a result of our methodology, it is possible to reduce environmental impacts substantially (up to 25 percent or more) while increasing operating costs only slightly (about two to four percent). These results are predicated upon situational factors such as fleet composition, system loading, and vehicle-specific costs and environmental parameters. We felt the need to produce a large amount of empirical data in preparation to prove our concept. We feel that the results presented in this report are adequate to demonstrate the potential benefits of the methodology.

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## INTRODUCTION

The environmental impacts of transportation are significant; and, these impacts are even more significant when examined on a life-cycle basis. When examined on this basis, it is also clear that anticipated "clean" fuels and technological innovations of the future, alone, do not provide the complete solution for minimizing transportation environmental impacts or providing environmentally sustainable transportation systems. For example, consider "zero emitting" electric vehicles, which transfer emissions from the tailpipe to the electric utility, or the much-heralded "fuel cell," which requires a hydrogen source that must be produced and distributed by some means. This is to say, even with cleaner fuels, other aspects of transportation system design and operation must also be addressed if overall or life-cycle environmental impacts of transportation systems are to be minimized.

From this analysis, it might be inferred that one key to minimizing the life-cycle environmental impacts of transportation is simply to minimize the transportation activity itself, since many of the direct and indirect environmental impacts are a function of, or can be attributed to, vehicle operation. While this is true conceptually, it is not feasible to implement in many circumstances, for example, in public transportation and commercial freight hauling systems that are operated because of statutory requirements or to service an anticipated demand. Typically, systems such as these utilize a fleet of vehicles—not uncommonly, a fleet comprised of different types of vehicles, e.g., having different capacities or capabilities. Here, the controllable environmental impacts of operation are affected by vehicle assignment and/or scheduling decisions. However, in a (heterogeneous fleet) system such as this, the relationship between vehicle activity, e.g., travel distance to satisfy a particular demand, and environmental impacts is situational and dependent upon vehicle parameters and the vehicle assignment including itinerary. In other words, the vehicle assignment and routing that minimizes distance or economic cost may not be the one that minimizes environmental impacts. Moreover, the environmental impacts are a function of variables in addition to travel distance alone. However, by considering these impacts to be a function of scheduling decisions, and including them in the scheduling optimization function, these impacts can be optimized (minimized) jointly with other decision variables.

The assignment or dispatching of vehicles in fleet operations entails vehicle routing, vehicle scheduling or a combination of both, following the taxonomy of Bodin and Golden (1981). And, problems such as these have been extensively studied by Operations Researchers over the years. However, there has been only very limited research to-date where environmental considerations have been included in the vehicle routing and scheduling objective function and optimization algorithm. In particular, there has been virtually no research of this type that has included environmental impacts assessed on a life-cycle basis.

In this paper, we present a methodology for optimizing vehicle routing and scheduling based on the joint optimization of cost, service, and life-cycle environmental impact parameters. We develop the methodology for a demand-responsive (also known as "dial-a-ride" [DAR]) transit system. In the U.S., the Americans with Disabilities Act requires municipal transit operators to accommodate disabled patrons. And, for a variety of reasons including safety and schedule maintenance, many municipalities have elected to do so through the provision of complementary transit (also known as paratransit), allowable under federal law, rather than by modifying existing bus fleets. While paratransit is only a small component of public transit overall, the number of miles traveled in the U.S. has doubled over the past ten years to nearly 600 million miles per year, according to the National Science and Technology Council (NSTC, 1998). And, demand for such services is expected to grow as the population ages demographically. More importantly, "high operating costs and poor management strategies that do not optimize the use of drivers and vehicles have made such services costly and less than fully responsive to their riders' mobility needs" (NSTC). These same underlying factors would be expected to affect the environmental impacts of operation, as well, the joint optimization of paratransit cost, service, and environmental performance.

Transportation Environmental Impacts

At the present time, 107 areas of the U.S. are not in compliance with one or more of the Ambient Air Quality Standards established by the federal Clean Air Act, including those for carbon monoxide (CO), nitrogen dioxide (NO2), sulfur dioxide (SO2), ozone (O3), lead (Pb), and particulate matter (PM-10) (United States Environmental Protection Agency [USEPA], 2002). And, a significant contributor to these air quality problems in the U.S. is transportation. According to USEPA (1999), about two-thirds of all CO emissions, and about one-third of all NOx and VOC emissions, nationwide, are attributable to transportation sources. Additionally, vehicles emit numerous toxic organic compounds, some of which are carcinogenic, including benzene, 1,3-butadiene, formaldehyde, ethyl benzene, methyl t-butyl ether (MTBE), hexane, acetaldehyde, styrene, toluene, and xylene. And, for these specific substances, highway vehicles are responsible about for one-quarter to one-half of total U.S. emissions, depending upon the pollutant (USEPA, 2000, 1996a). In addition, diesel-powered vehicles emit particulates comprised of numerous poly-cyclic and poly-aromatic hydrocarbons that are potent carcinogens, as well as ultra-fine particles that that are respiratory irritants (USEPA, 2000). Finally, the combustion of fossil fuels results in carbon dioxide and other greenhouse gas emissions; and, as of 1993, highway vehicles were responsible for about 23 percent of anthropogenic carbon dioxide emissions in the U.S. (USEPA, 1996a).

There has been substantial research investigating vehicular emissions, which are widely known to be a function of modal conditions (e.g., Hothersall and Salter, 1977). Specifically, emission rates are a function of vehicle speed, engine loading (power output), rate of acceleration or deceleration, etc., as well as mechanical factors such as carburetion and vehicle maintenance (TRB, 1995). Significant emissions also occur during engine starts as well as engine idling (CARB, 2000, 1998, 1996).

The environmental impacts of transportation are even more significant when they are examined on a life-cycle basis. Environmental life-cycle analysis (LCA) is a systematic approach and set of methods and techniques for the identification and assessment of environmental impacts and consequences over the complete life cycle of a product or process. The Society of Environmental Toxicology and Chemistry (SETAC, 1993, 1991) is generally credited for the current LCA methodological framework; and, recent ISO standards (ISO 14040 et seq.) have further formalized LCA. Moreover, the use of LCA to properly identify and characterize the environmental impacts and consequences of a product, process, or activity is recommended by USEPA (e.g., Keoleian and Menerey, 1994, 1993). In the case of transportation vehicles, for example, life-cycle impacts include not only those due to operation (e.g., tailpipe emissions), but also those due to vehicle production, the production of components and materials used in vehicle maintenance as well as the maintenance activity itself, and the impacts due to the "fuel cycle"—the extraction, refining, and distribution of motor fuels—to name just a few. And, the impacts in these other life-cycle stages may be significant. For example, DeLuchi (1993, 1991) found that VOC, NO2, and SO2 emissions from the "fuel cycle" to be comparable to those from the tailpipe on a normalized or "per mile" basis. Highly insightful discussions of the life-cycle stages and impacts of transportation systems are provided by USEPA (1999, 1996a), Keoleian, et al (1997), and Graedel and Allenby (1998). From these analyses, it is clear that the reduction of transportation environmental impacts requires consideration of the impacts over all life-cycle stages.

Vehicle Routing and Scheduling with Environmental Considerations

There has been extensive prior research investigating and modeling the environmental impacts, primarily emissions, of vehicle operation, due in part to Clean Air Act requirements. More recently, primarily in the context of Intelligent Transportation Systems (ITS), researchers have developed combined traffic simulation/emissions models for more accurately predicting vehicle emissions based on actual (simulated) modal conditions. Descriptions of numerous traffic/emissions models in current use may be found in FHWA (1992); USEPA (1998); Barth and Norbeck (1996, 1994); Feng, et al (1997); Shaheen, et al (1998); and Abdulhai, et al (1999).

There has also been limited prior work in the area of multi-objective network optimization, including that based on environmental impacts (tailpipe emissions), utilizing the previous models. In general, this research—including that of Tzeng and Chen (1993); Bededek (1995); SWUTC (1996); Yu (1996); Feng (1996); Kim (1995); Shaheen, et al. (1998); Benedek and Rilett (1998); Yu and Stewart (1995); and Johnston and Rodier (1999)—has focused on optimization of vehicle routing based on various traffic assignment principles and algorithms. That is, individual vehicles (representing origin-destination pairs) were assigned routings on simulated traffic networks so as to optimize particular objective functions. However, the previous research has generally been limited to optimization of specific pollutants (tailpipe emissions) individually and has not considered impacts on a life-cycle basis. More importantly, as Yu and Stewart have observed, there remains a genuine need to develop optimization models and approaches based on "a generalized cost function that includes both travel-time variables and the environmental variables."

Insofar as the problem of fleet vehicle routing and scheduling as we have described it, i.e., where environmental impacts are included among the optimization objectives, we have found only isolated examples in the literature of prior work in this area. One example is that of Eriksson, et al. (1996), who considered the use and/or assignment of vehicles (from among two types) for the delivery of newspapers, where they identified and optimized criteria pollutant emissions on a partial life-cycle basis. Thus, in this sense, their analysis may be considered as a type of vehicle routing problem. There have also been numerous projects, utilizing ambient air quality data and other ITS technologies, to reroute traffic (either through automated traffic control or provision of information to drivers) around intra-urban areas where pollutant levels are high. (See, for example, Taylor and Herbert, 1993 and Sommerville and Bostock, 1994, respectively, for descriptions of the Advanced Transportation Telematics and APOLLON projects in Europe and Iwaoka, et al., 2000 and Yoshiura, et al., 1999 for a discussion of the Universal Traffic Management Systems 21 in Japan.) We are not aware, however, of any prior work that has provided a methodology and algorithm for the scheduling of paratransit (or other fleet) vehicles based on the joint optimization of cost, service, and environmental impact objectives—in particular, where the latter are evaluated utilizing life-cycle impact assessment (LCIA) methods.

## Problem Description and Solution Approach

The objective of our research is to develop and demonstrate a methodological approach and vehicle routing/scheduling algorithm for the joint optimization of paratransit system performance including life-cycle (LCIA-based) environmental impacts (consequences). This would allow, for example, the operator of such a system to operate it in a manner that optimizes cost and service performance while simultaneously minimizing the environmental consequences of operation. We demonstrate the methodology through computer simulation of a paratransit system operation, where the modeled system is loosely based on an ACCESS Services (paratransit) provider in Los Angeles County. In order to accomplish the research objective, several developments are required and are listed below. The listing also provides a general outline of the remainder of this paper. The developments are:

1) Development of an environmental life-cycle model of paratransit operation and a life-cycle inventory (LCI) of operational environmental impacts as a function of vehicle itinerary (route/schedule) parameters;

2) Identification and quantification of the consequences of these impacts utilizing life-cycle impact assessment (LCIA) methods, as the basis of optimization;

3) Development of a multi-objective decision model with which to assess the relative desirability of alternative itineraries;

4) Translation of the decision model to an optimization model, and modification of existing DAR routing/scheduling algorithm to include the (previous) environmental consequences;

5) Simulation of paratransit operation and the vehicle scheduling algorithm.

## PARATRANSIT LIFE-CYCLE MODEL

We consider a hypothetical paratransit operation comprised of four vehicle types, including a gasoline-powered "minivan," a CNG-powered "minivan," and larger capacity "shuttle busses," gasoline- and diesel-powered. We assume generic, 1998-2000 model-year "light duty" or "medium duty" vehicles for which data is available. We utilize MacLean's (1998) life-cycle model of an automobile as the basis for our life-cycle model, although it is necessary to adapt it to the particular activity being modeled. Notably, MacLean's LCI model combines process impacts—vehicular emissions—with those determined using aggregated (economy-wide) data, specifically, data from the Economic Input Output-Life Cycle Assessment (EIO-LCA) model developed by Lester Lave and colleagues at Carnegie Mellon University (Hendrickson, et al., 1998).

In actual paratransit operation, environmental impacts (primarily tailpipe emissions and fuel consumption) arise due to vehicle usage and are a direct function of distance traveled. However, significant operational (process) impacts also arise from other aspects of vehicle operation including engine idling and engine starts. And, these latter impacts are a function of the vehicle itinerary (i.e., vehicle scheduling decisions), but are unrelated to the vehicle travel distance (which is also a function of itinerary). The life-cycle model for the paratransit operational process is shown in Figure 1. It should be noted that when a life-cycle inventory (LCI) is developed for the process, LCI impacts are allocated on a "per mile," "per engine start," and "per minute idling" basis.

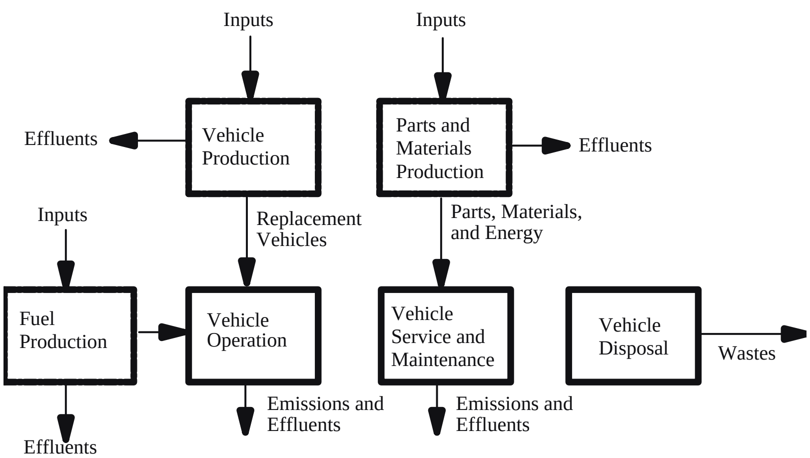



Figure 1. Paratransit Operation Life-Cycle Model

Vehicle running emissions are modeled utilizing the California Air Resource Board (CARB) (2000, 1998) EMFAC/Burden model. This is a regional emissions inventory model; however, we run the model including only vehicles (in the model's database) for Southern California for the model years and generic vehicles noted before, and using the default values for all of the other model inputs. It should be noted that the results are based upon the model's modified Federal Test Protocol drive cycle; i.e., taking into account different modal conditions. (This allows us to simulate transit using constant "average" speed, while still calculating emissions reflecting typical modal conditions.) Additionally, it is well known that the VOCs of tailpipe emissions are comprised of numerous toxins and carcinogens, such as benzene, toluene, formaldehyde, 1,3-butadiene, acetaldehyde, and others. We utilize data from the literature (e.g., USEPA, 2000; Winebrake and Deaton, 1999; Black, et al., 1998; Carslaw and Fricker, 1995; McCormick, et al., 2000; and Nylund and Lawson, 2000) to estimate these components of emissions from gasoline- as well as CNG- and diesel-powered engines. Finally, diesel emissions—in particular, the particulate and aerosol component—are known to be comprised of potent carcinogens, mostly in the form of poly-aromatic or poly-cyclic compounds. We differentiate diesel particulates (denoted as DPM-10) from particulates emitted from other sources (denoted as PM-10) in our model for this reason.

To estimate the impact (life-cycle inventories) for the other life-cycle stages, we utilize the EIO-LCA model and database available from Carnegie Mellon University, at the Green Design Initiative (2001) website at http://www.eiolca.net. Environmental impacts determined by the model include criteria pollutant, global-warming, and ozone-depleting emissions; non-renewable energy consumption; base and precious metal ore depletion; non-hazardous and RCRA waste generation; and Toxic Release Inventory (TRI) emissions. In the case of the latter, the Carnegie Mellon researchers devised an equivalency measure—based on American Conference of Governmental and Industrial Hygienists (ACGIH) Threshold Limit Values (TLVs) (Horvath, et al., 1995). The results of our life-cycle inventory analysis, with impacts summed over all life-cycle stages, are presented as Table 1 (where reported TRI emissions are on a CMU-Equivalent Toxicity basis). Details concerning the calculation and basis of these values are provided in Appendix A.

## LIFE-CYCLE IMPACT ASSESSMENT BASIS

From a decision-theoretic perspective (e.g., Keeney, 1992, 1988), it is not the impacts (e.g., tailpipe pollutant emissions) per se that are the basis for concern or the appropriate basis for optimization. Rather, it is the consequences of these impacts—e.g., human health and ecological damages—that are the basis for caring and should be the optimization basis. This is also consistent with the overall SETAC (1993, 1991) LCA framework, which provides for the following LCA steps:

- Inventory. The development of a detailed listing of all material and energy inputs and outputs, including quantities, having an environmental impact;

- Classification. Identification of indicator or impact categories and assignment of inventory components to the impact categories;

- Characterization. Analysis of the impacts/impact categories in terms of human health damage, ecological damage, and resource depletion (end-point effects);

- Valuation. Assignment of relative weights or priorities to each of the end-point effects, allowing, in effect, a single "score" to be calculated and used for prioritizing alternatives.

Additionally, the SETAC framework allows for LCA to be performed at different levels of analysis, including loading (Level 1); equivalency (Level 2); toxicity, persistence, and bio-accumulation (Level 3); and exposure/effects assessment (Levels 4/5). Equivalency analysis (sometimes called "mid-point" analysis) considers only impact categories (e.g., global warming) and the potential to cause damage (e.g., global warming potential). Exposure/effects analysis (sometimes called "damage function" or "end-point" analysis) includes identification of the cause-consequence chains and considers end-point damages (e.g., human morbidity and mortality) caused by the impacts (categories) considered in the analysis. (For future reference, we denote the former analyses as providing measures of damage potential and the latter analyses as providing measures of potential damage.) An informative overview of current LCA and LCIA practice may be found in Curran (1996).

Within this overall framework, the classification, characterization, and valuation of environmental consequences are performed in the life-cycle impact assessment (LCIA) step of LCA. Recently, numerous LCIA suites—including models, methods, databases, and, often, companion software—for this purpose have appeared and are in common usage. (Reviews of these are provided by Jensen, et al., 1997, and Postlethwaite and de Oude, 1996.)

From both the practical and theoretical perspectives, there are many contemporaneous issues associated with these LCIA methods, such as what the results represent insofar as actual damages that may be accrued (Owens, 1999, 1997a, b; Goedkoop and Spriensma, 2000a, b; Besnainou and

Coulon, 1996); which method is "best" for a particular application or analysis, since the methods do not provide data for identical sets of compounds ("stressors" in SETAC terminology) or end-point damages (e.g., Hertwich, et al., 1998; Notarnicola, et al., 1998); and the decision-theoretic validity of the valuation "formulas" that are prescribed by some of the methods (Miettinen and Hämäläinen, 1997; Seppälä, 1998; and Seppälä and Hämäläinen, 2001). Because of issues such as these, it has been suggested within the LCA technical community (Bare, et al., 2000) that LCIA results based on multiple methods (levels) of analysis might be used together to facilitate better, or, at least, more informed decision-making. For example, an analysis by Swanson, et al. (2000) found the damage indicators from several LCIA methods and levels of analysis to be complementary in nature; and, the use of data from multiple methods is intuitively appealing.

We address these issues in the next section of this paper, where we develop a decision-theoretic model. For now, what is important to understand is that the damage indicators (both mid-point and end-point) provided by the previous LCIA methodologies provide performance measures or attributes (representing environmental damages or consequences) for use in our decision and optimization models. That is, attributes are used to measure the levels of achievement of the stated objectives. We first identify the specific LCIA methods to be used, along with unit damage indicator values, for the stressors identified in the LCI (Table 1), and then consider their use as decision attributes. Finally, we use the results of the decision model (in the next main section) as the basis for specifying necessary weighting constants in the vehicle routing and scheduling objective function.

<u>Selection of Proxy Attributes for Human Health and Ecological Damages</u>

Shown in Tables 2 and 3 are indicator values, for the stressors listed in Table 1 (LCI), from several popular LCIA methods and/or sources: EPS (Steen, 1999a, b); Eco-Indicator (Goedkoop and Spriensma, 2000a, b); human and ecological toxicity potentials developed by Huijbregts, et al. (2000), based on the Uniform System for Evaluation of Substances (USES) LCIA model; and acidification and eutrophical potentials reported by Huijbregts (1999a). Also included in the Tables are potentials (equivalency factors) for global warming, photochemical oxidant creation, and acidification (USEPA, 1996b; CML, 2001) as well as hazard scores for human, aquatic, and terrestrial toxicity, based on USEPA's (1994) hazard assessment methodology. The indicators were selected to include both end-point and mid-point damages, i.e., representing potential damage and damage potential, as these terms were defined previously, chosen as representative of LCA methods in current, popular use. While the final form and appearance of the decision model(s) we develop are predicated on the indicators selected, we point out that other indicators could have been utilized just as well. That is, our purpose is to provide a methodological approach for the construction and evaluation of decision models utilizing indicators from multiple LCIA methods as opposed to a prescription for a specific model.

Several important points should be noted before we proceed further. First, the values shown in the Tables, in particular, for end-point indicators such as those from the EPS and Eco-Indicator methods, are unit values and are the "raw" indicator values provided by the methodologies before application of the methodologies' weighting or normalization factors. We develop our own weighting factors for the decision model that we develop, next. Second, as explained in the notes accompanying the Tables, we have combined the various EPS human morbidity and mortality indicators into a single constructed attribute "Calculated Disability-Adjusted Life-Years" (CDALYs) following an approach developed by Murray and Lopez (1996, reported in Goedkoop and Spriensma, 2000a). Similarly, we combined the various EPS indicators for (crop, wood, fish/meat) productive capacity losses into a similar constructed attribute "Productive Capacity Losses." We did this at this point as a matter of convenience and based on assumed decision-maker preferences. However, as seen in the decision model presented in the next section, we would have had to perform such aggregation at some other stage of the decision model evaluation if we had not done so here. (For a discussion of constructed attributes, their use in decision analysis, and their specification and evaluation, see Keeney, 1992.) Third, we follow Owens' (1999, 1997a, b) and Besnainou and Coulon's (1996) view that the damage indicators provided by the previous LCIA methods provide performance indicators, albeit useful for comparative analyses, rather than precise predictions of actual damages that will be accrued. As such, following Keeney's terminology, decision attributes defined based on these indicators are proxy attributes. Finally, it might be noticed that the stressors identified in Table 1 include certain resource consumptions (e.g., base metal) and other impacts (e.g., RCRA and solid wastes) for which data is not provided in Tables 2 and 3. The reason for this, which will be seen later, is that we use these impacts and quantities directly in the decision model; and, this is also why we have focused our attention on human health and ecological damages exclusively up to this point.

## DECISION-THEORETIC BASIS AND MODEL

Because of the underlying differences and limitations in the LCIA methods above, we wish to utilize the data (damage indicators) from multiple methods and levels of analysis in our decision model, as suggested by Bare, et al. (2000). And, we develop a decision model utilizing data from multiple LCIA methods based on decision-theoretic principles. We note, however, that our objective is a *decision model* utilizing various LCIA damage indicators and not the de facto synthesis of a new LCIA *damage assessment model*. That is, we do not wish to alter the various methods' impact categories, damage functions and indicators, and internal stressor and damage allocations.

The decision problem as described thus far is a classic formulation in multi-objective multi-attribute (MOMA) decision analysis, where the decision objectives include not only environmental damages but also cost- and service-related objectives, which we add to the model later. Numerous, theoretically rigorous methodologies such as utility theory (e.g., Fishburn, 1970, 1964; Keeney and Raiffa) or T.L. Saaty's (1977) analytic hierarchy process (AHP) are available for such problems (see, also, Seppälä, et al., 2002.) For the problem at-hand, we assume a typical decision-maker willing to trade off accomplishment of the objectives above, consistent with current LCA practice. Moreover, the valuation formulas of current LCIA methods such as EPS and Eco-Indicator should be seen to be utility-based (e.g., Seppälä, 1998; Seppälä and Hämäläinen, 2001). Thus, to maintain consistency with current LCA practice and LCIA methods, we choose utility theory as the basis on which to develop our decision model.

Unlike most other decision methods, multi-attribute utility theory, based on the game theory of von Neumann and Morgenstern (1947), also provides a rigorous treatment of decision-maker attitude toward risk (i.e., probabilistic outcomes). (We follow the convention that "utility" models describe preferences for outcomes that are probabilistic and "value" models describe preferences for outcomes that are deterministic.) A theoretical discussion of utility theory's axiomatic basis may be found in Luce and Raiffa (1957). Because we are considering the damage indicators provided by LCIA methods as proxy measures for actual damages (where minimization of the latter is our true or fundamental decision objective), we develop the decision model as a utility model. We also assume a decision-maker who is risk-neutral, in part, to maintain consistency with current LCIA methods. And, we assume that the other requisite conditions for a valid utility function hold (e.g., as described in Luce and Raiffa, 1957).

Basic Decision Model

We follow Keeney's approach, overall, for the specification and hierarchical structuring of fundamental decision objectives. Following SETAC (1993, 1991), we specify the highest-level objectives as minimization of Human Health Damage, Ecological Damage, and Resource Depletion; and, we add the additional objective of minimization of Other Impacts to address those impacts from Table 1 (e.g., solid and RCRA wastes) for which consequence (damage) data is unavailable. As suggested by Bare, et al. (2000), we consider both mid-point and end-point indicators, i.e., damage potential and potential damage, for the human health and ecological categories; and, we specify these as sub-objectives. The basic decision model (objectives hierarchy) as developed thus far is shown in Figure 2, where the relationship between objectives and attributes (LCIA damage indicators from Tables 2 and 3) is also shown. In the Figure, the $w_i$'s are preference-based weighting or scaling constants. Additionally, we have combined Huijbregts, et al.'s (2000) various (USES-LCA-based) ecological toxic potential indicators (from Table 3) into a single constructed attribute, Eco-Toxicity Potential, following a procedure that we describe next.

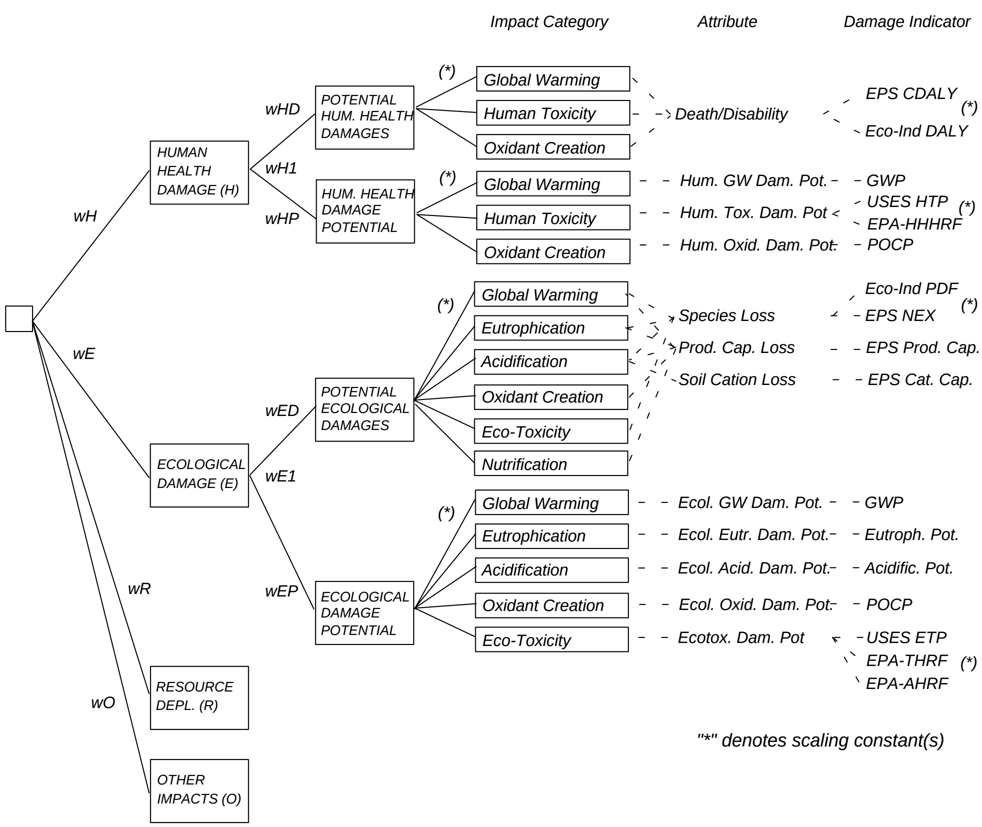



Figure 2. Basic Decision Model

Aggregation of Proxy Attributes

From a theoretical perspective, there are two significant, related issues that must be addressed in order to aggregate LCIA damage indicators as decision attributes as implied in Figure 2. First, decision-maker preferences must be assessed based on actual consequences (Keeney, 1992), even though the damage indicators, as proxy attributes, provide only an imprecise measure of them (e.g., Owens, 1999, 1997a, b). Second, the underlying models from which the damage indicators are derived are not identical and consider different intermediate impact categories, damage functions, etc. That is, in order to combine damage indicators (as proxy attributes) from multiple LCIA methods, it is necessary to make *factual-based judgments* comparing the magnitude of *actual* damages represented by the respective indicators, in consideration of the methods' underlying damage models. Ordinarily, this would not be a consideration in the combination of indicators from a single LCIA method. In our decision methodology, we address both of these issues; however, for brevity, we present only the highlights (below) as well as the final result.

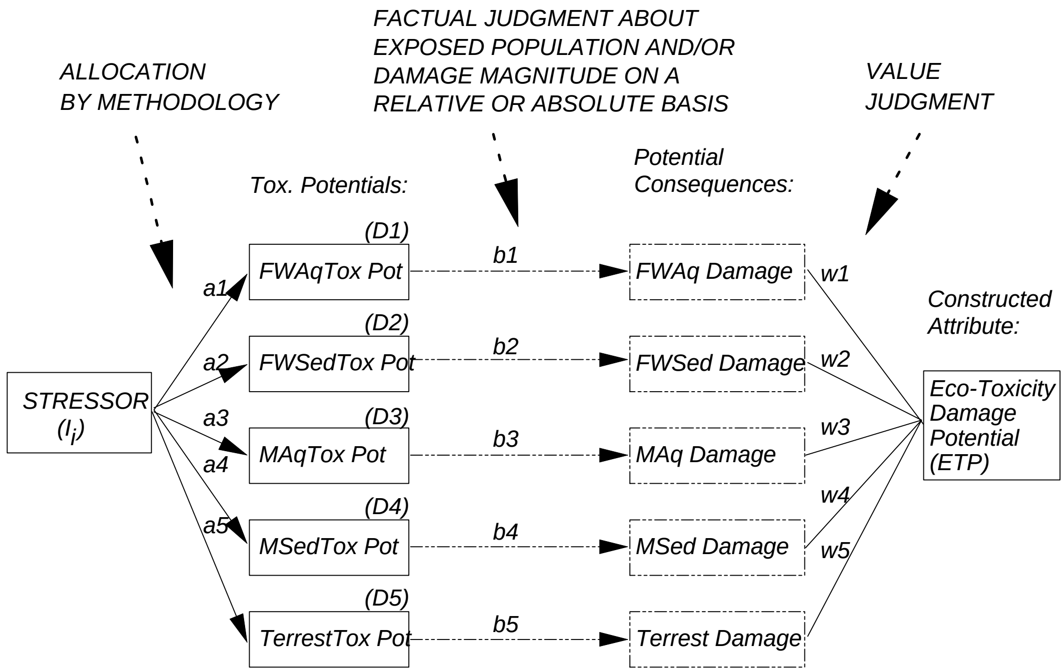
We use Huijbregts, et al.'s (2000) various ecological toxicity potentials (Table 3)—specifically, their combination into a single constructed attribute, Eco-Toxicity Potential—to illustrate our overall methodological approach for aggregating proxy attributes with the above considerations in mind. Keeney (1992) provides an illuminating discussion of the problems associated with the use of proxy attributes, in particular, the need for the decision-maker to make a combination of factual-based judgments (pertaining to the levels of actual consequences associated with the proxy values) and value-based judgments (concerning the relative desirabilities of the actual consequences). This combination of judgments is problematic according to Keeney. And, he provides an approach wherein the judgments are decoupled and the factual-based judgments are made on a probabilistic basis. While Keeney's approach could be applied to the problem at-hand, we expect many decision-makers would have difficulty elucidating the required probability distributions. Moreover, we feel the imprecision that is associated with LCIA damage indicators as predictors of actual damages is more aptly treated as *vagueness* than as probabilistic uncertainty. Specifically, we utilize (fuzzy) linguistic variables to represent the actual consequences as *possible*, rather than probable, outcomes, based on Zadeh's (1978) representation of fuzzy sets as *possibility distributions*, where we also implicitly assume that the requisite von Neumann and Morgenstern axioms concerning probabilistic outcomes hold for possibilistic outcomes, as well.

Our overall procedure is illustrated in Figure 3; however, we note again that this procedure is also utilized in other aggregation steps when the decision model is evaluated. We calculate the <u>unit damage indicator</u>, Ecological Toxicity Potential (USES-ETP), denoted as $D_{ij}$, value for each substance i listed in the LCI (Table 1), as

$$\boldsymbol{D}_{ij} = \sum_k [(w_k \boldsymbol{b}_k D_{ijk}) / (\sum_k w_k \boldsymbol{b}_k)], \qquad (1)$$

where $w_k$ has already been normalized. The $D_{ijk}$'s are the substance- and compartment-specific USES-LCA unit damage indicators (listed in Table 2). (Notationally, the subscript "j" is used to identify damage indicators and associated decision attributes; if USES-ETP were the only damage indicator in the decision model, there would be no need for the subscript. And, the subscript "k" denotes impact categories or compartments, e.g., marine sediment. Fuzzy quantities are indicated in bold-italic typeface.)

*Aggregation of USES-LCA Ecological Damage Indicators As a Constructed Attribute*




Figures 3. Model for Evaluation of Constructed Attributes with Value and Factual Judgments De-Coupled

Values of $\boldsymbol{b}_k$, representing factual judgments concerning the magnitude of *actual* consequences associated with the compartment-specific indicators, are represented using normal, triangular fuzzy numbers representing linguistic variables. For example, the decision-maker may compare *actual* consequences associated with Huijbregts, et al.'s, specific potentials using linguistic variables such as "much greater," "about the same," etc. (See Figure 4.) Further, in Huijbregts, et al.'s methodology, toxicity potentials are calculated based on a single reference substance (1,4-dichlorobenzene). In other words, only one $\boldsymbol{b}_k$ based on 1,4-dichlorobenze is assessed for each damage compartment. Finally, following LCIA and utility theory conventions, we assume that value-based judgments, comparing consequence desirability and used to evaluate the $w_k$ constants, can be made on a scalar basis.

Decision-Maker Preference Assumptions, Evaluation of Single-Attribute Utility Functions, and Overall Utility Equation Forms

Before we can proceed to specification of the final decision model, including aggregation of attributes based on damage indicators from multiple LCIA methods, we address some prerequisite matters concerning decision-maker preferences (assumptions) and resultant utility equation forms. First, following the convention of current LCIA methods, we assume that single-attribute (unidimensional) utility functions have a constant rate of (utility) substitution; i.e.,

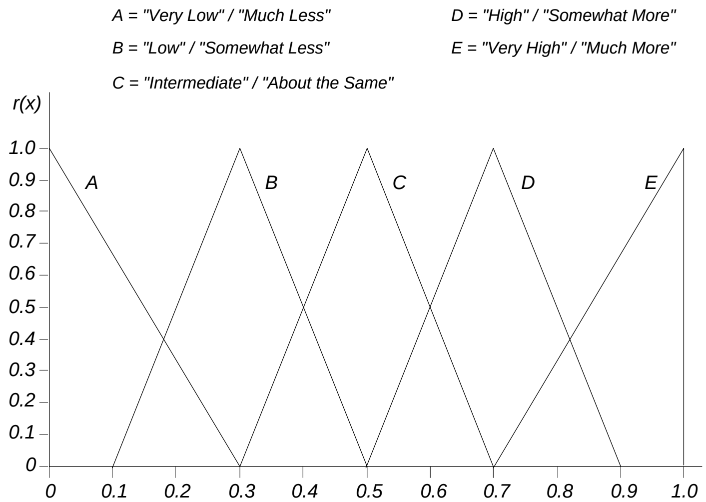



Figure 4. Linguistic Variables for Damage Comparison

single-attribute utility functions are linear. For example, let $D_j$ denote the value of (potential damage or damage attribute) attribute j. Then,

$$u(D_j) = - [D_j - D_{j(BEST)}] / [D_{j(WORST)} - D_{j(BEST)}], \qquad (2)$$

where $D_{j(WORST)}$ and $D_{j(BEST)}$ denote the "worst" and "best" values of attribute j, respectively, among the alternatives considered. Note that we have defined the utility scale such that 0 is "best" and –1 (or "about minus 1" in the case of fuzzy numbers) is "worst." However, in our (paratransit scheduling) application we do not know the "best" and "worst" values of $D_j$ a priori. Instead, we define reference values based on estimation of the best and worst possible scheduling scenarios. We define $D_{j(BEST)} = 0$ and redesignate $D_{j(WORST)}$ as $D_{jREF}$. Then, because of assumed linearity of the unidimensional utility function,

$$u(D_j) = - D_j / D_{jREF}. \qquad (3)$$

For an attribute based on a single LCIA methodology, we evaluate the attribute following the methodology's convention. In general, attribute ($D_j$) values, representing "total" damage or damage potential of type j, are calculated as:

$$D_j = \sum_i I_i D_{ij} = \sum_i \sum_k I_i D_{ijk}, \qquad (4)$$

where $I_i$ is the quantity of stressor i (from the LCI), $D_{ij}$ is the stressor-specific unit damage indicator for stressor i and attribute (damage type) j, and $D_{ijk}$ is the stressor-impact-specific unit damage indicator if such is provided by the methodology. Here, in the case of end-point or damage function LCIA methods (such as EPS and Eco-Indicator), the allocation of stressor i over the modeled impact categories and damages is performed by the methodology (and is reflected in the unit damage values, to facilitate the previous type of calculation); and, we do not alter these allocations. In the case of attributes based on mid-point or damage potential indicators (e.g., global warming potential), we allocate the stressor quantity 100 percent to each applicable impact category following USEPA (1996b, 1994).

Utility theory provides for the combination of preferences for multiple attributes (representing multiple objectives) into a single value as:

$$u(x_1, x_2, \ldots, x_n) = f[u_1(x_1), u_2(x_2), \ldots, u_n(x_n)], \tag{5}$$

where the actual form of $f[u_i(x_i)]$ is predicated upon whether certain preference independence conditions (among attributes) are met. In the case of utility functions, if the attributes $X_i$ are additive independent (which also implies mutual utility independence among attributes), an additive utility decomposition form may be used, i.e.,

$$u(x_i) = \sum_i w_i\, u_i(x_i), \text{ where } \sum_i w_i = 1. \tag{6}$$

That is, the preference (level) for an alternative is the simple sum of the appropriately scaled preference levels of each attribute comprising the alternative. If attributes $X_i$ are each mutually utility independent (only), a multiplicative form may be used, i.e.,

$$Ku(x_1, x_2, \ldots, x_n) + 1 = \prod_i^n [Kk_i u_i(x_i) + 1]. \tag{7}$$

Both are special cases of the multi-linear utility function (see Keeney, 1992, for a proof),

$$u(x_1, x_2, \ldots, x_N) = \sum_{i=1} k_i u_i(x_i) + \sum_{i=1}\sum_{j>1} k_{ij} u_i(x_i) u_j(x_j) + \sum_{i=1}\sum_{j>i}\sum_{h>j} k_{ijh} u_i(x_i) u_j(x_j) u_h(x_h) + \ldots \tag{8}$$

Because of the large number of attributes for which preference independence would have to be tested, we, instead, limit consideration to the additive and multiplicative forms as recommended by Zeleny (1982) and Keeney and Raiffa (1993), including the nesting of such forms within a larger overall model, as these forms have been shown to provide robust representations of decision-maker preferences. As a consequence, we assume attributes to be either additive or mutually utility independent (only).

From the above discussion and the objectives structure of Figure 2, our intended direction may be inferred. Namely, let the following denote decision sub-objectives (with associated attributes):

H ≡ Human Health Damage
E ≡ Ecological Damage
R ≡ Resource Depletion
O ≡ Other Impacts
HD ≡ Human Health Potential Damages
HP ≡ Human Health Damage Potential
ED ≡ Ecological Potential Damages
EP ≡ Ecological Damage Potential.

Then, from the objectives structure in Figure 2, we define utility functions such that:

$$u(\text{itinerary}) = f[u_H(H), u_E(E), u_R(R), u_O(O)], \quad (9)$$

where

$$u_H(H) = f[u_{HD}(HD), u_{HP}(HP)] \quad (10)$$

$$u_E(E) = f[u_{ED}(ED), u_{EP}(EP)], \quad (11)$$

and where these individual utility functions are evaluated utilizing the damage indicators (as attributes) shown in Figure 2.

Following current LCIA practice, we assume the highest-level attributes of Equation 9 to be additive independent. In simple terms, additive independence implies that the preference order for alternatives is dependent only on the values and associated uncertainties of the attributes individually and not in combination. (See Keeney, p. 134, for a more precise and technical definition.) And, we also see this assumption as reasonable for the aggregation of attributes <u>within</u> the individual damage potential and potential damage utility functions, i.e., evaluation of $u_{HP}(HP)$, $u_{HD}(HD)$, $u_{EP}(EP)$, and $u_{ED}(ED)$.

However, current LCIA practice does not provide guidance insofar as the combination of *damage potential* and *potential damage* attributes. Here, we provide for the possibility (although not necessity) that a decision-maker's preference for the values of one set of attributes is not independent of the values and uncertainties (technically, as lotteries, or in this case, as possibility distributions) involving the other set of attributes. And, we assume only the weaker condition of mutual utility independence.

The result of these assumptions is that we may specify a decision model of overall form:

$$u(\text{itinerary}) = w_H\, u_H(H) + w_E\, u_E(E) + w_R\, u_R(R) + w_O\, u_O(O), \text{ where} \quad (12)$$

$$u_H(H) = w_{HD}\, u_{HD}(HD) + w_{HP}\, u_{HP}(HP) + (1\text{-}w_{HD}\text{-}w_{HP})\, u_{HD}(HD)u_{HP}(HP), \quad (13)$$

$$u_E(E) = w_{ED}\, u_{ED}(ED) + w_{EP}\, u_{EP}(EP) + (1\text{-}w_{ED}\text{-}w_{EP})u_{ED}(ED)u_{EP}(EP), \quad (14)$$

where $w_H + w_E + w_R + w_O = 1$, all other terms are as defined previously, and where equations for evaluation of $u_R(R)$, $u_O(O)$, $u_{HD}(HD)$, $u_{HP}(HP)$, $u_{ED}(ED)$, and $u_{EP}(EP)$ remain to be defined.

Finally, we note one important point concerning the utility functions above and assessment of scaling constants. Because of certain assumed preference conditions (decision-maker risk neutrality and additive independence among attributes within each of the HD, HP, ED, EP, R, and O damage domains), utility functions and value functions (i.e., based on deterministic outcomes) assessed over these domains must be coincident. Specifically, since we are also assuming a decision-maker who is <u>risk-neutral</u>, where $u(x) \sim v(x)$, a utility function ($u[x]$) assessed over an additive value function ($v[x]$) must also be additive. This means that if we were assessing preferences for an actual decision-maker, once we have determined that the decision-maker is risk-neutral, we can assess preferences based on deterministic outcomes (rather that lotteries involving uncertain outcomes) and induce utility functions over the assumed (linear) value functions. Similarly, it allows us to combine utility functions and value functions directly. Had these preference conditions not been the case, we would have had to assess utility functions based on uncertain outcomes or estimated the functions from assessed value functions and assessment of the decision-maker's risk tolerance. (Procedures for both may be found in Keeney and Raiffa, 1993) Additionally, we note one important distinction between value and utility functions: value functions provide cardinal measures, while utility functions provide only ordinal measures, insofar as strength of preference (Keeney, 1992). That is, differences of utility values do not have cardinal meaning.

Evaluation of End-Point Damage-Based Utility Functions, $u_{HD}(HD)$ and $u_{ED}(ED)$

As seen in Figure 2, we evaluate the end-point damage-based utility functions, $u_{HD}(HD)$ and $u_{ED}(ED)$, based upon the damage indicators provided by the EPS and Eco-Indicator LCIA methodologies. However, the problem that arises is that the two methods, even though generally considering the same stressors and impact categories, do not assign the stressors identically to the same impact categories, as is more clearly seen in Figures 5a and 5b. Hence, the resultant indicators, e.g., for species loss (NEX and PDF, respectively), are not comparable measures. In other words, decision-maker factual judgment insofar as the *magnitude of actual damages* represented by each proxy measure for each stressor is necessary. However, if we followed the methodologies' conventions and aggregated damage indicators across stressors (Equation 4) first before calculating utility values (Equation 3), the differences between the two methods would be masked by the aggregation and there would be no basis on which to make the necessary factual judgments.

A direct solution to this problem may be found by combining Equations 3 and 4. Specifically, it should be seen (in the case of damage indicators from a single LCIA method) that

$$u(D_j) = - [\sum_i I_i D_{ij} / D_{jREF}] = \sum_i u(D_{ij}), \qquad (15)$$

where $u(D_{ij}) = - I_i D_{ij} / D_{jREF}$. and $D_{ij}$ is the stressor-specific unit damage indicator for stressor i, as before. This is true because of the assumed linear single-attribute utility function, the linear manner in which the methods combine stressor- and impact-specific damage indicator values, and the way that $D_{jREF}$ has been defined. The quantity $u(D_{ij})$ may be thought of as a "partial utility value," attributable to stressor i, and where the utility value (of an alternative) taking into account all stressors is the sum of the partial utility values. Thus, to combine indicators from multiple (EPS and Eco-Indicator) methods, we follow an approach similar to that previously utilizing linguistic-based factual judgments. (We also adjust the "spread" of the fuzzy variables to reflect the relative degree of imprecision associated with the methodologies. In this case, because the indicators and methods provide less imprecise indicators than before, we use narrower "spreads.") Let $A_{Xl}$ denote a decision attribute ($X \in$ HD, ED damage domains, $l = 1, 2, \ldots$) and $a_{Xli}$ be the value of $A_{Xl}$ for stressor i. Then:

$$\boldsymbol{u}_{Xli}(a_{Xli}) = - \sum_j \{I_i \sum_k [(D_{ijk})(\boldsymbol{b}_{Xlijk})] / D_{j(REF)}\}, \qquad \forall\, D_j \in A_{Xl} \qquad (16)$$

where the $\boldsymbol{b}_{Xlijk}$ values are normalized values representing factual judgments as to the relative significance (in terms of *actual* damages) associated with each damage indicator $D_{ijk}$, evaluated for each damage type j and stressor i. For example, Human Health Potential Damage is evaluated based on one attribute $A_{HD1}$ ($l = 1$), which, in turn, is evaluated utilizing the EPS CDALY and Eco-Indicator DALY damage indicators (e.g., $D_{j=1}$ and $D_{j=2}$). Values of $\boldsymbol{b}_{HD1ijk}$ are ascribed for each stressor i and impact category k (global warming, human toxicity, oxidant creation; k=1, 2, 3). Assumed values of $\boldsymbol{b}_{HD1ijk}$ are provided in Table 4 to illustrate the process. Finally, the partial utility values are then aggregated over all stressors as:

$$\boldsymbol{u}_{Xl}(a_{Xl}) = \sum_i \boldsymbol{u}_{Xli}(a_{Xli}), \qquad \text{for X = HD, ED.} \qquad (17)$$

Values of $u_{HD}$(HD) and $u_{HP}$(HP) and then calculated simply as:

$$\boldsymbol{u}_X(X) = \sum_l w_{Xl}\boldsymbol{u}_{Xl}(a_{Xl}), \qquad l = 1, 2, \ldots; \sum_l w_{Xl} = 1; \text{ for X=HD, ED.} \quad (18)$$

In the above calculations, it should be seen that we are aggregating fuzzy quantities, in the calculation of utility values, as fuzzy weighted averages, i.e., as $\boldsymbol{r} = (\sum_{l=1}^{L} \boldsymbol{w}_l u_l(A_l)) / (\sum_{l=1}^{L} \boldsymbol{w}_l)$. (See, for example, Klir and Yuan [1995].)

<u>Evaluation of Mid-Point Damage-Based Utility Functions, $u_{HP}$(HP) and $u_{EP}$(EP)</u>

The procedure for evaluation of the mid-point-based damage potential utility functions, $\boldsymbol{u}_{HP}$(HP) and $\boldsymbol{u}_{EP}$(EP), is more or less similar to the previous procedure with certain exceptions. From Figure 2, the two constructed attributes, Human Toxicity Damage Potential (based on the damage indicators USES HTP and EPA-HHHRF) and Eco-toxicity Damage Potential (based on the damage indicators USES-ETP, EPA-THRF, and EPA-AHRF) are first evaluated. In the first case, because both indicators provides measures of the same *type* of damage potential (human health), only factual judgments are required and partial utility values may be calculated using Equation 16. In the latter case, both value- and factual-based judgments are required, since the indicators represent different types of damage potentials. In this case:

$$\boldsymbol{u}(a_{Ej}) = - \sum_k \{[h_{Ek}\, \boldsymbol{e}_{Ek}\, (DP_{jk} / DP_{jk(REF)})] / [\sum_k h_{Ek}\, \boldsymbol{e}_{Ek}]\}, \qquad (19)$$

where $h_{Ek}$ and $\boldsymbol{e}_{Ek}$ are value- and factual-based weighting constants, respectively (e.g., as in Figure 3). Single-attribute utility values for all other lowest-level attributes, $u(a_{Xj})$, evaluated based on a single damage indicator, may be evaluated following Equation 3. Utility values for the decision attributes $B_X$, where X = HP, EP, are evaluated as

$$\boldsymbol{u}_X(B_X) = \sum_j \{[c_{Xj}\, \boldsymbol{d}_{Xj}\, u(a_{Xj})] / [\sum_j c_{Xj}\, \boldsymbol{d}_{Xj}]\}, \qquad (20)$$

where $c_{Xj}$ and $\boldsymbol{d}_{Xj}$ are value- and factual-based weighting constants, respectively. (Values of $c_{Xj}$ and $h_{Ek}$ are normalized because of the assumed linear-additive decomposition form. Normalized values of $\boldsymbol{e}_{Ek}$ and $\boldsymbol{d}_{Xj}$ may also be used; however, it should be seen in Equations 19-20 that it is the product, e.g., $\sum_j c_{Xj}\, \boldsymbol{d}_{Xj}$, that is normalized in the calculation itself.)

The most important difference in this case is that the value- and factual-based scaling constants are <u>not assessed for each stressor i</u>. Rather, they are ascribed based upon the impact category, as it is assumed that the equivalency factors on which the damage indicators are based take into account stressor-specific differences.

<u>Evaluation of Resource Depletion and Other Impacts Utility Functions, $u_R$(R) and $u_O$(O)</u>

Utility values for Resource Depletion and Other Impacts objectives (attributes) are calculated directly from the LCI quantities (Table 1). In the case of the latter, we do this because of the lack of readily available consequence data, and, in the case of the former, because of the lack of consensus damage measures within the LCA community (e.g., Guinee and Heijungs, 1995; Hertwich, 1996). (However, this does not obviate entirely the need for the decision-maker to consider the consequences of these impacts, i.e., in the assessment of weighting constants.) We also assume that the attributes comprising the Resource Depletion and Other Impacts objectives to be additive (and mutually utility) independent, allowing simple, linear-additive utility functions to be defined for each. Following the previous nomenclature:

$$u_R(R) = \sum_j w_{Rj}\, u(D_j), \qquad \forall\ D_j \in R,\ \sum_j w_{Rj} = 1 \qquad (21)$$

$$u_O(O) = \sum_j w_{Oj}\, u(D_j), \qquad \forall D_j \in O,\ \sum_j w_{Oj} = 1 \qquad (22)$$

$$u(D_j) = -\,(D_j / D_{j(REF)}), \qquad D_{j(REF)} \geq \max[D_j] \text{ among alternatives} \qquad (23)$$

$$D_j = \sum_i I_i\, D_{ij}, \qquad \forall\ D_j \in R,\ \forall\ D_j \in O; \quad D_{ij} = 1 \text{ if } D_j \in \{R, O\}, 0 \text{ otherwise.} \qquad (24)$$

It should be seen in the above that $D_{ij}$ in this case is a dummy variable used to maintain consistency of nomenclature <u>and</u> to provide for the use of damage indicators other than stressor quantity in the decision model, if desired. Finally, we note that the utility functions above are, technically, *value functions*, as there is no uncertainty of outcome involved.

Evaluation of Value- (Preference-) Based Weighting Constants

We assume that value- (preference-) based scaling constants, representing the relative *desirabilities* of the attributes (as consequences), can be assessed on a scalar basis, following LCIA and utility theory practice. Techniques for the elicitation of decision-maker preference may be found in Pöyhönen and Hämäläinen (1997) as well as Keeney and Raiffa (1993). Importantly, these constants are relative to, and must be assessed based upon, the range of outcomes (i.e., the reference values) considered (Keeney, 1992). Also, importantly, the scaling constants ($w_k$'s) must be evaluated utilizing preference, i.e., u(x) values as opposed to attribute (x) values, in order to identify points of preference indifference. Keeney and Raiffa (1993) provide a rigorous approach for the assessment of scaling constants. Procedurally, their approach entails the comparison of changes of attribute values (e.g., $\Delta x_1$ and $\Delta x_2$) and corresponding changes of utility values, i.e., $\Delta u_1(\Delta x_1)$ and $\Delta u_2(\Delta x_2)$, to find values of $\Delta x_1$ and $\Delta x_2$ such that $\Delta u_1(\Delta x_1) = \Delta u_2(\Delta x_2)$ (from which weighting constants can be calculated), where the consequence scales are normalized scales.

Calculation of Itinerary (Environmental) Utility Function Values and Defuzzification of Results

For any itinerary, the transit distance, engine idling time, and number of engine starts can be determined. (Engine idling and starts occur at nodes, following an assumed paratransit service/ operational policy. This is discussed later.) LCI impacts for an itinerary are calculated by multiplying the previous quantities by the unit impact factors provided in Table 1 for the applicable vehicle type. Damage indicator (attribute) values are calculated by multiplying the resultant impact quantities by the unit damage indicator values provided in Tables 2 and 3 (i.e., Equation 4). And, the itinerary utility value (Equation 12) is calculated utilizing the utility relationships described in the Sections 4.2 through 4.6.

From the various equations, it should be seen that certain of the calculated intermediate quantities are (normal, triangular) fuzzy numbers. However, because fuzzy numbers cannot be ranked or ordered as scalar numbers can, they must be defuzzified on some basis. As a general rule, because the fuzzy number (set) contains distributional information, we do not defuzzify calculated values until after the final calculation, to avoid loss of this information. (For a discussion of fuzzy arithmetic calculations, as well as defuzzification algorithms, see, for example, Klir and Yuan, 1995.) For this purpose, we use the common Center of Area (COA) defuzzification algorithm, which returns the support (x- or abscissa) value of the centroid of the fuzzy possibility distribution, i.e., $x_c = (x_1 + x_2 + x_3) / 3$, where $x_1$, $x_2$, and $x_3$ are the x- values of the vortices. In the case of a triangular fuzzy number (a, b, c), it should be seen that the x- values correspond to the quantities a, b, and c, respectively.

Decision Model Translation for Use in Optimization – Calculation of "Unit Partial Utility Values"

Using the decision model just presented, the utility value of an itinerary (in terms of environmental consequences) may be calculated based upon the transit distance, engine idling (minutes), and number of engine starts resultant of the itinerary. In terms of the utility calculation, these variables are independent variables (notwithstanding the fact that there are a function of the itinerary itself). And, rather than performing all of the previous calculations repeatedly, it is desirable to transform the model from a decision model to an optimization model, i.e., based on the previous independent variables:

$$u(\text{itinerary}) = f(\text{Distance, Idling, Engine Starts, Vehicle Type}). \qquad (25)$$

From the previous equations, it should readily be seen that if the calculated single-attribute utility value for any damage indicator (attribute $D_j$) is –x for one mile of travel, it will be –2x for two miles of travel, etc., because of the linearities that exist in the calculation of damage values and single-attribute utility functions. Similarly, the same result will hold for the LCI quantities expressed in "per minute engine idle" and "per engine start" units. Further still, the utility functions $u_{HD}(HD)$, $u_{HP}(HP)$, $u_{ED}(ED)$, $u_{EP}(EP)$, $U_R(R)$, and $U_O(O)$ are also each evaluated utilizing linear-additive combinations of the respective, single-attribute utility functions, i.e., the $u(D_j)$'s, from which they are evaluated. The point is that these functions can be evaluated once for each vehicle type and each vehicle operational unit, i.e., a mile of travel, a minute of engine idling, and an engine start. And, Equations 12-14 (for calculating the itinerary utility value) may then be evaluated directly from these unit quantities together with the known number of respective units, i.e., miles of transit, minutes idling, and number of engine starts. Illustrative values of these "unit partial utility factors," calculated based upon values of factual- and value-based weighting constants that we have assumed for a hypothetical decision-maker, are provided in Table 5. Details of the calculation of these values are provided in Appendix B. Values of assumed decision-maker weighing constants may be found in Appendix C.

## PARATRANSIT OPERATION, MODELED SYSTEM AND MULTI-OBJECTIVE SCHEDULING ALGORITHM, AND EXPERIMENTAL DESIGN

In general, paratransit service is provided "door-to-door"; that is, the client is picked up at a requested location and transported to a desired location. In this regard, service is similar to taxi service. However, unlike taxi service, ridesharing (combining multiple, non-related clients having non-identical origins and destinations) is allowed. Moreover, increasing ridesharing is seen as key to improving productivity (Dessouky and Adam, 1998a). Also in general, two types of service requests are provided for: advance requests and same-day ("ASAP" or "immediate") requests. Planned vehicle routes (itineraries) for advance requests typically are determined in advance. However, the planned routings must then be modified dynamically and in real-time to accommodate same-day or "ASAP" requests. The latter task, called dispatching, may be facilitated with the aid of certain ITS technologies, such as automatic vehicle location (AVL) and geographic information systems (GIS). Because of clients' physical disabilities, specially equipped vehicles—in particular, those than can accommodate wheelchair-bound patrons—are utilized. It should be noted, however, that not all clients are necessarily wheelchair-bound, and that paratransit fleets are often composed of multiple vehicle types for this reason.

Paratransit providers must comply with certain standards, including those prescribed in regulations as well as in contractual terms. For example, the provider may be penalized (e.g., by the transportation authority) if the provider refuses "appropriate" service requests or misses agreed upon time windows (for example, +/- 15 or 20 minutes of the agreed upon time). Conversely, the provider may receive performance incentives based on service and economic performance, e.g., productivity and utilization of resources. In practice, ride requests are assigned to vehicles in a manner that minimizes an objective function comprised of cost and service performance objectives. (See, for example, Chira-Chavala, 1999 and Dessouky and Adam, 1998a.)

<u>Paratransit Vehicle Scheduling</u>

The paratransit (DAR) optimization problem is a problem in combinatorial optimization and is a combined vehicle routing and scheduling problem as described before. Following the taxonomy of Psaraftis (1980) and Jaw, et al. (1986), the paratransit problem of interest is "many-to-many" (origins and destinations), multi-vehicle, and having time windows. Specific cases of the problem include static (advance reservation) scheduling and dynamic (immediate service) dispatching. There may also be additional constraints, including service constraints (e.g., maximum ride times), vehicle capacity, as well as precedence and other logical constraints. Numerous algorithms for DAR routing and scheduling have been developed and reported in the literature, generally for simplified versions of the real-world problem. Overall, the algorithms (where time windows are assumed) can be dichotomized based upon whether they are for the static or dynamic case, for single- or multiple-vehicle systems, and exact or heuristic.

Early research to develop scheduling algorithms was generally based on the construction and solution of minimum spanning trees and/or Traveling Salesman Problem (TSP) tours. Psaraftis (1983, 1980), for example, provides both exact and heuristic solutions for the single vehicle case, for both static and dynamic requests, where, in the case of the latter, the tour was reoptimized every time a new request was received. Stein (1978) provided an analytical examination of both single- and multi-vehicle fleets, considering both the static and dynamic cases. He proposes a two-step approach of clustering or partitioning of requests followed by individual tour construction. However, his focus was on optimal partitioning versus solution of the resultant TSP problem. More recently, Ioachim, et al. (1995) modeled the problem as a pick-up and delivery problem with time windows (PDPTW), which they solve in several steps. However, their solution, too, involves the solution of a resultant TSP problem, which they solve by a column generation method.

While exact solutions to the TSP problem are available (e.g., based on Hamiltonian cycles), the problem is NP-hard, meaning that the number of iterations that must be performed increases non-polynomially with the size of the problem. For this reason, heuristic scheduling algorithms are generally utilized in practice; and, two areas of development are of particular note. The first is the development of "insertion" algorithms (e.g., Jaw, et al., 1986; Madsen, et al., 1995; Toth and Vigo, 1997), where requests are tentatively inserted into existing vehicles' schedules on some heuristic basis, with the preferred insertion being the one that minimizes the objective function of interest. These algorithms can be used to construct initial vehicle itineraries for static requests as well as to modify them dynamically. The second development of note is the development of post-insertion optimization procedures (e.g., Gendreau, et al., 1994, 1992), applicable to itineraries constructed using insertion-type as well as other algorithms.

Modeled Paratransit System and Operation

In the modeled paratransit system, service is provided on a "24/7" basis through the use of shifts. Modeled vehicles can accommodate certain numbers of wheelchair and "regular" patrons, where the capacity of each is fixed. And, the fleet is comprised of different types and sizes of vehicles—with each vehicle type having specific capacities for each type of patron as well as specific (non-identical) economic costs of service and environmental impacts. Two types of requests are provided for: "immediate" and "advance," where the latter are those received in excess of five hours before the requested pick-up time. Advance requests are scheduled at the beginning of the shift (the first shift on which they could be serviced.) That is, "skeleton" itineraries are created based on the advance requests. Immediate requests are scheduled when received. In our model, transit speed is deterministic and is the same for all vehicles (28 mph, the average transit speed in Los Angeles). However, loading and unloading times are stochastic. It is assumed that the position and status of all vehicles is known at all times; and, the scheduling of immediate requests takes into account the vehicles' actual statuses.

Time windows are applied to pick-up times (only); and, "maximum ride time" is imposed as a feasibility constraint to prevent excessive ride times (drop-off times) due to indirect routing. For a pickup, the "on-time" window is defined as -x/+y minutes of the requested (assigned) pick-up time, where the "late" window (y) is different for immediate and advance requests. This is a "soft" window, meaning service will proceed no matter how late the vehicle arrives. The "early" window, which is the same for both types of requests, is a "hard" window. If a vehicle arrives before the window (before –x minutes), the vehicle waits and service begins at the "early" window, i.e., -x minutes of the requested pick-up time. Monetary penalties are applied if the vehicle arrives at the pick-up location early or late, i.e., outside of the on-time window. In the modeled system, all vehicles originate and return to a central depot. Overtime is not allowed; and, vehicles must return to the depot by the end of the shift.

Service requests are generated randomly and are not known a priori. Request parameters—including origin and destination locations, requested pick-up times, call-in times, and number and type of patron (wheelchair and non-wheelchair)—are random variables, where the distributional parameters that are used are based on actual data provided by ACCESS Services, Inc., and reported in Dessouky and Adam (1998a, b). Experimental values of these and the previous parameters are provided in Table 6.

Simulated vehicle operation is governed by certain service polices. First, vehicles depart service nodes as soon as service (loading/unloading) is completed and proceed to the next scheduled node, unless the last service node is also the last node on the itinerary. In this case, they wait at the last service node (which must be a destination node), either until another request is received or until such time that the vehicle could depart and return to the depot at the end of the shift. Additionally, vehicles en route between service nodes are not rerouted dynamically. Finally, insofar as engine idling and starting, drivers allow the engine to idle during loading and unloading. Similarly, drivers allow the engine to idle at pick-up nodes if the vehicle must wait (because the vehicle is early) and there are passengers already on-board. (This is done for passenger comfort, e.g., to allow operation of the vehicle's air conditioner or heater as well as other devices.) On the other hand, if the vehicle arrives at a pick-up node early and there are no passengers already on board, the driver is assumed to turn off the vehicle's engine and restart it at the time boarding begins. (These considerations do not apply to drop-off nodes, as unloading begins immediately when the vehicle arrives at the node.)

Simulation Model and Model Verification/Validation

To simulate operation of the modeled system, we developed an event-based simulation program written entirely in Microsoft® Visual Basic™ 6.0, where "events" include the scheduling of a service request and the arrival of a vehicle at a service node (because of stochastic loading/unloading times). In execution, the program constructs *planned* itineraries, which are converted during the course of the simulation to *executed* itineraries as a result of "events." That is, when an event occurs, the affected vehicle's itinerary—specifically, planned times subsequent to the event time—may be affected and are modified accordingly. The model makes extensive use of data files, recording all aspects of vehicle itineraries (times and node sequences) as well as request-related service data. These files are used for the calculation of simulation statistics and were used significantly for debugging and model verification. Additionally, the program includes extensive error traps, which were also used for model verification.

To validate the model and program, we compared the simulation results to those of a similar model—based on the same overall request, service, and experimental parameters and paratransit system—and insertion algorithm previously reported by Dessouky and Adam (1998a). For validation purposes, we ran the model with the environmental parameters and values set to zero, and utilizing the same request data (file) as Dessouky and Adam. We then compared the results based on the key performance measures reported by Dessouky and Adam previously. (The measures include those reported in Section 6.)

Basic Real-Time Scheduling Heuristic

We adapt Dessouky and Adam's (1998a) scheduling objective function to the modeled service policies and penalties described above. Specifically, their algorithm is an implementation of Jaw, et al.'s (1986) parallel insertion algorithm. And, based on the modeled system, we define the objective function based on the weighted summation of three itinerary-related costs: 1) transit cost (based on itinerary distance), 2) lateness penalty (if the vehicle arrives at the pick-up location after the on-time window), and 3) earliness penalty (if the vehicle arrives at the pick-up location before the on-time window).

Modification to Include Environmental Impacts

We next modify the previous heuristic to include environmental impacts. Although we have not stated this explicitly before, we use utility (theory) as the basis for aggregating economic costs and environmental consequences, as they are in different units and there is no consensus approach or data by which to monetize all environmental consequences. Our objective function is of the form:

$$\text{maximize } u(\text{service of requests}) = w_C\, u(\text{economic cost}) + w_E\, u(\text{environmental impact}). \qquad (27)$$

Let {R} be the set of requests for service to be scheduled and $r_i$ be the $i^{th}$ request for service. The provision of service (for request $r_i$) incurs both an economic cost (denoted as $CS_i$) and an "environmental cost" (denoted as $EC_i$). The scheduling objective, generally speaking, is to minimize the combined values of $CS_i$ and $EC_i$ over {R}, i.e., maximize $\sum_{i\in R} u(CS_i, EC_i)$. (The utility values are calculated as *disutility*, i.e., negative values; thus, the objective is to maximize these values.)

Applying the same (additive independence) preference assumptions as before, the objective is:

$$\text{maximize } \sum_{i\in R} u(CS_i, EC_i) = \sum_{i\in R} [w_{CS}u(CS_i) + w_{EC}u(EC_i)]. \qquad (28)$$

Let $CS_{ij}$* denote the total economic cost of all vehicles' itineraries (i.e., as Equation 26) after insertion of $r_i$ into vehicle j's itinerary; and let $EC_{ij}$* denote the environmental system "cost" of all vehicles' itineraries after insertion of $r_i$ into vehicle j's itinerary. The basis for evaluation of $EC_{ij}$* and $u(EC_{ij}*)$ was discussed earlier. We calculate $u(CS_{ij}*)$ also utilizing reference values as before, i.e., $u(CS_{ij}*) = - CS_{ij}* / CS_{REF}$, where $CS_{REF}$ is the estimated "worst" system cost for the operational period.

An *exact* solution to this problem would require that either all $r_i$ were known a priori or that all vehicles' itineraries were reoptimized after each new request was received. And, since neither are feasible or practical, our optimization is heuristic and based on optimizing each request individually:

$$\underset{j}{\text{maximize}}\; u(CS_{ij}*, EC_{ij}*) = \underset{j}{\text{maximize}}\; [w_{CS}u(CS_{ij}*) + w_{EC}u(EC_{ij}*)] \qquad \text{for } \forall r_i \in \{R\}. \qquad (29)$$

Finally, before leaving this topic, we note one additional point that was alluded to earlier. We assume that u*tility* functions have only ordinal quality, even though under certain circumstances *value* functions, having cardinal quality, could be induced as described earlier. And, we do this so that our methodology is not predicated on any particular preference condition, i.e., decision-maker risk neutrality. Because of this, we cannot evaluate insertion costs (as utility values) on a marginal basis. Moreover, because the environmental utility function is non-linear and utility values are relative to the scale on which consequences are evaluated, the alternative that is "best" based on individual vehicle itinerary environmental impacts and associated scales may not, necessarily, be the "best" alternative when evaluated based upon system-wide environmental impacts and scales. And, it is the system-wide impacts of operation, rather than the impacts of any particular vehicle, that is the basis for caring, i.e., the preference basis. Thus, we determine the “best” insertion based on “total system” utility value, evaluated including all in-service vehicles and itineraries, for each request scheduled.

### Experimental Design

Values of experimental and other cost/service parameters are provided in Table 6; and, we only briefly discuss the experimental design here in terms of its purpose and overall strategy. Our primary purpose is to demonstrate that, through our methodology and the consideration of environmental parameters in the vehicle routing and scheduling process (i.e., algorithm), the overall environmental impacts of the operation can be substantially reduced. Additionally, we would like to demonstrate that this can be accomplished without equally substantial increases in operating “cost”—which we measure in units of utility as well as dollars and travel distance.

Because the system is stochastic and the variables used to measure system performance are random variables, we utilize the *method of independent replications* (e.g., Law and Kelton, 1991; Pritsker and O’Reilly, 1999) to reduce the variance of the simulation results. In the simulation program itself, because of the way that service requests are generated and the way the vehicle-shifts are accounted for, the transient effects that would be otherwise be expected to occur at system (simulation) start-up and shut-down have been eliminated. This is to say, we simulate paratransit operation as a *terminating* system; and, we can replicate single 24-hour operating periods with minimal transient effects that would affect the outcome.

We consider several fleet composition scenarios, where the fleet is comprised of at least two or more vehicle types (from the types in Table 1). And, we also consider the case of a homogeneous fleet. For each scenario, we compare the results—in terms of “cost” and environmental impact—based on scheduling using our algorithm versus those where only economic costs are considered (as in current paratransit scheduling algorithms). We also simulate various levels of system loading (by adjusting the number of available vehicles, since the number of requests per period is constant). Specifically, we would expect to find greater environmental improvement in a system having “surplus” vehicles (including “environmentally friendlier” ones) available. And, we also investigate the effect of varying the weighting constants in the objective function (Equation 29). All scenarios utilize the same sets of service requests.

## EXPERIMENTAL RESULTS

Simulation results, for the fleet compositions and fleet sizes (representing different levels of system loading) simulated, are provided in Tables 7 through 11. In the tables, the first row of each composition-size combination (shown in boldface) represents the “baseline,” that is, based on the scheduling algorithm (objective function) considering only economic costs. And, the rows immediately below each “baseline” case are results based on the new algorithm including environmental impact (Equation 29). We first consider the effects of the new algorithm in terms of service performance and then in terms of cost and environmental performance.

As seen in Table 7, together with the vehicle utilization results from Table 9, the three loading levels simulated represent cases of surplus capacity (surplus vehicles available), adequate capacity (all or most available vehicles utilized), and capacity shortage (unscheduled requests). It should also be observed that ridesharing (defined as the number of requests served divided by the number of trip starts) remains relatively constant over all cases and environmental weights, while vehicle utilization increases as capacity relative to demand decreases. In the case of the latter, this represents the elimination of "slack." This is further evidenced by the trend of increasing mean pick-up delay and decreasing on-time performance. However, taken together, we interpret the constancy of ridesharing as indicating ridesharing is primarily governed by the service and operational policies and constraints, together with the spatial and temporal distribution of requests, rather than by other factors such as capacity. Overall, it should be seen from Table 7 that the effect of increasing environmental weight in the objective function is to increase pick-up delays and decrease on-time performance.

The effects of the new algorithm in terms of cost and environmental performance may be seen in Table 8, as well as in Tables 10 and 11 comparing life-cycle environmental impacts. (From the regulatory perspective, in particular for Southern California, the criteria and other pollutant air emissions [Tables 10a and 11] represent the most significant impacts identified in the LCI [Table 1]. Moreover, when examined by life-cycle stage, up to one-half or more of the total life-cycle emissions, depending upon pollutant, are attributable to vehicle operation, service and maintenance, and fuel refining and distribution—all of which would be expected to occur in the Southern California region.) From Table 8, it should be immediately seen that the most significant improvement in terms of environmental impact (as utility value) relative to the "baseline"—both alone and relative to marginal cost increase—occurs at the smallest environmental weighting factor. That is, while further environmental improvement may (or may not) be possible, it comes with increasing marginal cost. Moreover, from Table 7, the service impacts are the least affected. Thus, we believe many decision-makers would find this case ($w_{ENV}$=0.125) to represent the best marginal "trade-off." And, we consider only this case in the remaining discussion.

Overall, the greatest environmental improvement (in terms of utility value and specific pollutants) is seen to occur in Case I, the heterogeneous fleet comprised of four types of vehicles. (This is also our primary case of interest.) And, improvement occurs at all three levels of system loading. For example, in the "best" (surplus vehicle) case, as measured in utility values, environmental performance is improved by about 33 percent while cost is increased by only about 4 percent. However, all Case I improvements (considering only the "baseline" and $w_{ENV}$=0.125 cases and based on utility value) are statistically significant at the 95 percent ($\alpha$=0.05) confidence level.(1, 2) Moreover, for this case, the apparent, slight cost increases for the first two loading levels are not statistically significant at the same confidence level.

Environmental improvements (as utility value) are also seen to result in Case II (heterogeneous fleet comprised of two vehicle types) at all system loading levels. And, all improvements are statistically significant at the 95 percent confidence level. (See Notes 1 and 2.) Finally, for the homogeneous fleet case (Case III), while Table 8 indicates very slight environmental (utility value) improvement at all three system loading levels, the improvement is not statistically significant.

Insights into the scheduling effects of the new algorithm may be obtained from the data in Table 9, where the most obvious effect is the shifting of vehicle selection, i.e., from "dirtier" to "cleaner" vehicles. And, this is seen to occur (in the heterogeneous fleet cases) at all system loading levels. Additionally, it should be seen that average distance and total number of vehicles utilized appear to decrease with increasing environmental objective weight—up to a certain point. This would be expected to be associated with increasing pick-up delays; and, this is seen to occur from Table 7. Finally, the number of engine starts and controllable (waiting) engine idling also appear to decrease slightly with increasing environmental objective weight.

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(1) We calculate the confidence interval for $\xi = \mu_1 - \mu_2$, i.e., the difference of means, where $\mu_j \approx E(X_j)$. However, in our simulation, we used the same sets of requests for each simulated case; and $X_{1j}$ and $X_{2j}$ would, therefore, not be expected to be independent. (However, $n_1 = n_2$.) Because of this, we use the "standard" paired-t confidence interval, defining $Z_j = X_{1j} - X_{2j}$, where the $Z_j$'s are assumed to be IID. (We calculate $Z_j$ using the results of individual replications, which are not reported in this paper, where $X_{1j}$ is the "baseline" case where $w_{ENV}=0$ and $X_{2j}$ is the case where $w_{ENV}=0.125$.) Then, $E(Z_j) = \xi$. And, the 100(1-$\alpha$) confidence interval for $Z_{MEAN}$ is $Z_{MEAN} \pm t_{n-1, 1-\alpha/2} [Var(Z_{MEAN})]^{1/2}$, where $Var(Z_{MEAN}) = \{\sum_{j=1}^{J} [Z_j - Z_{MEAN}]^2 \}/ n(n-1)$. (See, for example, Law and Kelton.) That is, we are relying on the Central Limit Theorem to imply that the coverage probability will be near 1- $\alpha$. However, according to Law and Kelton, the parametric approach is robust in this case, as any skewness in the underlying distributions will be eliminated upon subtraction. And, finally, we make the claim that differences in environmental performance (as utility value) are statistically significant if zero does not fall within the confidence interval. The calculated 95 percent confidence intervals for $\xi$, for the three cases (I, II, III) and fleet sizes, are:

| Case | Variable | 210 Veh. | 180 Veh. | 150 Veh. |
|---|---|---|---|---|
| I | u(env) | [0.1399, 0.1626] | [0.0676, 0.0835] | [0.0274, 0.0356] |
| I | u(cost) | [-0.0118, -0.0053] | [-0.0098, -0.0038] | [-0.0092, 0.0117] |
| II | u(env) | [0.0123, 0.0218] | [0.0050, 0.0108] | [0.0013, 0.0055] |
| II | u(cost) | [-0.0080, -0.0007] | [-0.0112, 0.0004] | [-0.0230, 0.0100] |
| III | u(env) | [-0.0018, 0.0065] | [-0.0009, 0.0047] | [-0.0025, 0.0027] |
| III | u(cost) | [-0.0074, 0.0000] | [-0.0109, -0.0015] | [-0.0119, 0.0067] |

(2) In order to perform the above comparisons, we must assume that differences of utility value have cardinal meaning, which is contrary to the point made earlier. In the case at-hand, utility functions do have cardinal meaning, as they were induced over valid value functions. However, in general, this may not be the case. Unfortunately, the only other way around this dilemma would be to calculate differences based on absolute quantities, i.e., pollutant emissions individually. We did this for the case of $NO_x$ emissions, because these emissions are a concern (precursor to smog and ozone formation) and we assume them to be "representative." And, we calculated paired-t confidence intervals as described in Note 1. We found the differences (e.g., Tables 10 and 11) to be statistically significant for all Case I and Case II fleet size scenarios. Differences for Case III were found not to be statistically significant except for the 210 vehicle scenario.

## CONCLUSIONS AND RECOMMENDATIONS

In this research, we developed a methodology for the combined routing and scheduling of fleet vehicles where environmental impacts, assessed using environmental life-cycle impact assessment (LCIA) methods, have been included in the scheduling algorithm and optimization objective function. And, we demonstrated the methodology for a demand-responsive ("Dial-a-Ride" or paratransit) transit application, where both vehicle cost and environmental impact parameters were assumed based upon generic classes of vehicles and literature data. Through simulation, we showed that substantial environmental performance improvements (emissions reductions) can be achieved for heterogeneous fleets, at various loading levels, with only minimal negative impacts on operational cost and service performance, which was our primary objective. (In the case of a homogeneous fleet, the environmental improvements were minimal and not statistically significant.) While we considered only certain specific heterogeneous fleet compositions, we believe the results are generalizable to other heterogeneous fleet compositions that might have been modeled based upon observed algorithm effects. Additionally, we note that the specific results are based upon the arbitrary allocation of vehicles (types) to the service shifts that were modeled. In other words, on those shifts where additional vehicles were available (because they were not on-duty at the time), further environmental impact reductions may have been possible through different "mixes" of allocated vehicle types. (It should be seen that there are trade-offs insofar as vehicle operating cost, environmental impact, and capacity. And, the "best" fleet composition is not, necessarily, a fleet comprised exclusively of the lowest-cost or "cleanest" vehicles available.)

The environmental impacts of fleet vehicle operation are influenced by many controllable and non-controllable variables and, of course, are a function of parameters specific to the specific vehicles and vehicle types comprising the fleet. One of these controllable variables is vehicle assignment including routing and scheduling. And, while our results can only be generalized so far, we believe they are adequate to demonstrate, for the generalized heterogeneous fleet case, that opportunities for reducing environmental impacts are available through vehicle routing and scheduling decisions, and that environmental performance can be jointly optimized with other operational (e.g., cost and service) objectives. We also note that the emissions data we used vary dramatically as a function of different driving patterns and cycles. We did not study the changes in driving cycle in this study.

The South Coast Air Basin (including Los Angeles County) is the only region in the country designated by USEPA as being in "extreme" non-attainment with the Clean Air Act Ambient Air Quality Standard (AAQS) for ozone. The area is also designated in the lesser category of "serious" non-attainment with the AAQS for particulates (PM-10). Moreover, a 1999 study by the SCAQMD (2002) found that up to 90 percent of the carcinogenic risk in the South Coast Basin due to air quality is attributable to mobile sources, primarily from diesel particulates and air toxics. We have shown that, in certain circumstances, all of these can potentially be reduced. (In the case of ozone, this is achieved through reduction of its precursors, $NO_x$ and VOCs.)

The methodology that we developed *could* be incorporated into existing paratransit scheduling software, although to do so, we would recommend the modifications discussed in the "Implementation" section. Moreover, the SCAQMD, under Regulation XXII ("Mobile Source Emissions Mitigation Programs"), provides funding for mobile source emissions mitigation projects where the emissions reductions are "real," "surplus," "quantifiable," and meet other criteria. That is, it is within the realm of possibility that SCAQMD funding might be obtainable by a paratransit provider, in conjunction with a paratransit scheduling software provider, to incorporate emissions reduction into paratransit scheduling software.

## IMPLEMENTATION

We envision the benefits of this research to be as follows:

1) We believe the primary benefit of this research is that it dispels the notion, for the case of a heterogeneous fleet, that environmental impacts (whether life-cycle based or based simply on criteria pollutant emissions) are solely a function of travel distance and are not affected by vehicle routing and scheduling decisions. While we see this research as being exploratory in some regards, as there has been virtually no prior research in this area, we hope that the results provide impetus to others to investigate potential applications, benefits, and limitations of the methodology.

2) We developed the methodology taking into account life-cycle environmental impacts and utilizing rigorous decision-theoretic methods. As noted above, the methodology could be incorporated into existing paratransit scheduling software. To facilitate this, we suggest:

    a) Limitation of impacts considered to criteria and air toxic pollutants, as these are of greatest concern in the South Coast Air Basin. (Additionally, global warming gases such as carbon dioxide could be included based on current legislation.) Moreover, while consideration of environmental impacts over all transportation life-cycle stages is required in order to achieve environmentally sustainable transportation systems, there are many jurisdictional and regulatory barriers that make this "systems approach" difficult to implement at the present. Therefore, we would suggest further limitation of impacts considered to tailpipe emissions.

    b) If limited to the above impacts, manufacturers' FTP certification data should readily be available and allow specification of emissions based on *actual* data for *actual* vehicle makes and models (e.g., as user input).

    c) The purpose of the decision model developed herein was to facilitate specification of weighting constants in the routing/scheduling objective function for the environmental impacts, e.g., tailpipe emissions as a function of vehicle itinerary, although this was perhaps obscured by the fact that the objective function was specified based on utility rather than emissions values. Nonetheless, an objective function could alternatively have been specified of the form $\sum_i w_i I_i$, where $I_i$ are the emissions of interest and $w_i$ are preference-based weighting constants. In the case of the latter, less formal and rigorous methods are available for determining or specifying these; and, we suggest use of these methods in any implementation of the methodology.

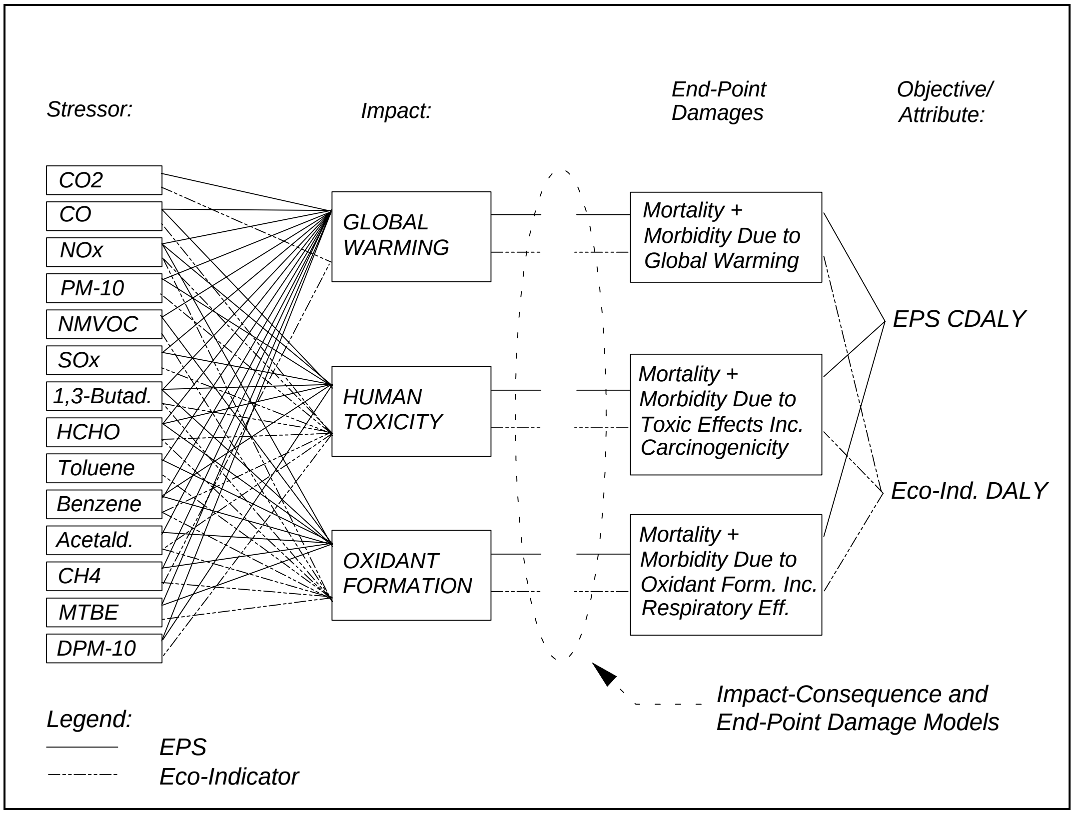


Figure 5a. Combined Fundamental and Means-Ends Network for Health Damages

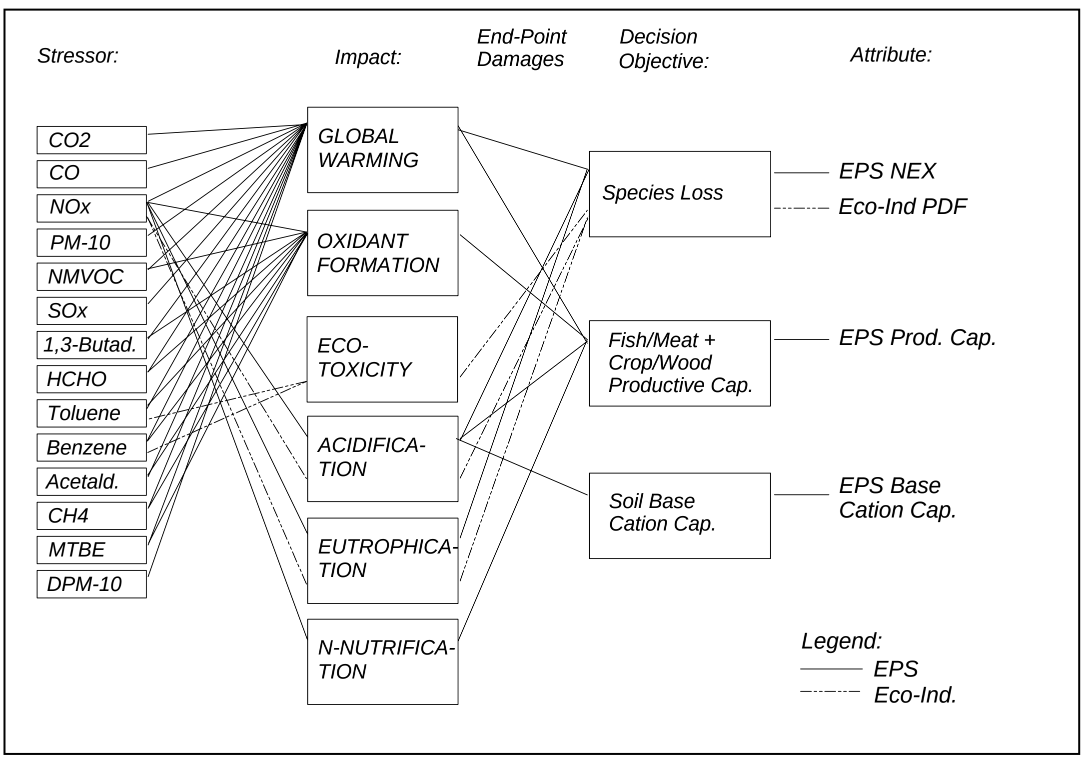


Figure 5b. Combined Fundamental and Means-Network for Ecological Damages

| Table 1. Life-Cycle Inventory for Modeled Vehicle Types | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Impact* | *LD Gasoline-Powered "Minivan"* | | | *LD CNG-Powered* "Minivan" | | | *MD Gasoline-Powered* "Shuttle Bus" | | | *MD Diesel-Powered* "Shuttle Bus" | | |
| | g/mile | g/min. | g/start | g/mile | g/min. | g/start | g/mile | g/min. | g/start | g/mile | g/min. | g/start |
| NMOG (VOC) | 0.4445 | 0.3041 | 0.2417 | 0.5600 | 0.0140 | 0.0092 | 0.6419 | 0.5189 | 0.5486 | 0.9862 | 0.1380 | 0.0940 |
| Methane | 0.0087 | 0.0526 | 0.0160 | 6.5400 | 0.3589 | 0.2480 | 0.0310 | 0.0749 | 0.0370 | 0.0176 | 0.0054 | 0.0037 |
| Formaldehyde | 0.0013 | 0.0088 | 0.0067 | 0.0180 | 0.0099 | 0.0068 | 0.0060 | 0.1450 | 0.0168 | 0.0519 | 0.0160 | 0.0109 |
| 1,3-Butadiene | 0.0003 | 0.0018 | 0.0013 | | | | 0.0012 | 0.0029 | 0.0034 | 0.0021 | 0.0006 | 0.0004 |
| Acetaldehyde | 0.0003 | 0.0018 | 0.0013 | 0.0020 | 0.0001 | 0.0001 | 0.0012 | 0.0029 | 0.0034 | 0.0104 | 0.0032 | 0.0022 |
| Toluene | 0.0060 | 0.0352 | 0.0276 | | | | 0.0243 | 0.0587 | 0.0674 | 0.0041 | 0.0013 | 0.0009 |
| Benzene | 0.0021 | 0.0123 | 0.0097 | | | | 0.0085 | 0.0205 | 0.0237 | 0.0021 | 0.0006 | 0.0004 |
| Methyl t-Butyl Ether | 0.0042 | 0.0176 | 0.0149 | | | | 0.0128 | 0.0309 | 0.0377 | | | |
| $SO_x$ ($SO_2$) | 1.083 | 0.068 | 0.046 | 0.928 | 0.005 | 0.003 | 1.203 | 0.121 | 0.054 | 1.077 | 0.083 | 0.057 |
| $NO_x$ ($NO_2$) | 1.088 | 0.189 | 0.408 | 1.714 | 0.145 | 0.0992 | 2.176 | 0.323 | 1.383 | 4.593 | 0.359 | 0.244 |
| CO | 3.025 | 6.248 | 2.959 | 2.669 | 0.036 | 0.0249 | 6.048 | 12.403 | 9.244 | 2.018 | 0.332 | 16.042 |
| GWP ($CO_2$ / $CO_2$-equiv.) | 867.2 | 154.0 | 104.3 | 936.2 | 32.3 | 22.2 | 1302.1 | 273.1 | 121.6 | 860.2 | 73.8 | 50.1 |
| PM-10 | 0.148 | 0.009 | 0.006 | 0.1466 | 0.023 | 0.0151 | 0.188 | 0.016 | 0.007 | 0.116 | 0.009 | 0.006 |
| Diesel PM-10 (DPM-10) | | | | | | | | | | 0.0601 | 0.0230 | 0.0156 |
| TRI air emissions | 0.042 | ≈ 0 | ≈ 0 | 0.044 | ≈ 0 | ≈ 0 | 0.038 | 0.001 | ≈ 0 | 0.041 | ≈ 0 | ≈ 0 |
| Non-renew. energy use (units in Mjoules) | 7.488 | 0.982 | 0.668 | 7.024 | 0.069 | 0.047 | 13.135 | 1.760 | 0.786 | 6.968 | 1.050 | 0.710 |
| Fuel use (in gasoline eq.) (Units in gallons) | 0.0498 | 0.0125 | 0.0086 | 0.0454 | 0.0010 | 0.0007 | 0.0889 | 0.0223 | 0.0100 | 0.0387 | 0.0157 | 0.0107 |
| Base-metal ore depletion | 66.682 | 0.520 | 0.354 | 71.280 | 0.037 | 0.025 | 60.119 | 0.929 | 0.415 | 65.804 | 0.553 | 0.376 |
| Prec.-metal ore depletion | 12.724 | 0.076 | 0.052 | 13.615 | 0.005 | 0.004 | 11.385 | 0..137 | 0.061 | 12.554 | 0.082 | 0.055 |
| RCRA Wastes | 1.466 | 0.051 | 0.035 | 1.525 | 0.004 | 0.002 | 1.468 | 0.092 | 0.041 | 1.428 | 0.055 | 0.037 |
| Non-recycled solid waste | 4.800 | | | 5.560 | | | 5.190 | | | 6.82 | | |

| Table 2. LCIA Equivalency and Hazard Ranking Factors | | | | | | | |
|---|---|---|---|---|---|---|---|
| Stressor | GWP (2) | POCP (3) | Acidification Potential (4) | Eutrophication Potential (4) | Human Health Hazard Ranking Factor (1) | Terrestrial Hazard Ranking Factor (1) | Aquatic Hazard Ranking Factor (1) |
| $CO_2$ | 1 | 0 | | | 0 | 0 | 0 |
| CO | 3 | 0.270 | | | 4.8 | 0 | 0 |
| $NO_x$ | 0 | 0.028 | 0.7 | 1.0 | 12.3 | 0 | 0 |
| PM-10 | 0 | 0 | | | 0 | 0 | 0 |
| (NM)VOC | 11 | 0.64 | | | 17.8 | 0.5 | 32.5 |
| $SO_x$ | 0 | 0.048 | 1.0 | | 3.6 | 0 | 0 |
| 1,3-Butadiene | 11 | 0.85 | | | 43.8 | 1.8 | 46.8 |
| Formaldehyde | 11 | 0.52 | | | 70.2 | 12.6 | 28.2 |
| Toluene | 11 | 0.64 | | | 12.2 | 0 | 24.0 |
| Benzene | 11 | 0.22 | | | 38.7 | 0 | 25.2 |
| Acetaldehyde | 11 | 0.64 | | | 27.0 | 3.3 | 19.5 |
| Methane | 24.5 | 0.006 | | | 0 | 0 | 0 |
| Methyl t-Butyl Ether (MTBE) | 11 | 0.175 | | | 1.2 | 1.2 | 1.2 |
| DPM-10 | 0 | 0 | | | 37.0 | 0 | 71.2 |

(1) Hazard ranking values from USEPA (1994). DPM-10 value based on anthracene. VOC value based on xylene (mixed isomers). Values for CO, $NO_x$, $SO_x$ estimated on $LC_{50}$.
(2) GWP values taken from Steen (1999a).
(3) POCP values taken from CML (2001). VOC value based on toluene.
(4) Acidification and eutrophication values taken from Huijbregts (1999) and USEPA (1996b).

| Table 3. LCIA Damage Function Indicators by Impact Category | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Stressor** | **Impact Category and Indicator Type and Value** | | | | | | | | |
| | | | | | Human Toxicity | | | | |
| | Global Warming | | | | Toxicity | Oxidant Formation | Carcinogenic Effects | Respiratory Effects | Toxic Potential |
| | EPS-CDALY | Eco-DALY | EPS-Prod.Cap. | EPS-NEX | EPS-CDALY | EPS-CDALY | Eco-DALY | Eco-DALY | USES-HTP |
| $CO_2$ | 1.30E-6 | 2.10E-7 | -3.97E-2 | 1.26E-14 | | | | | |
| CO | 3.91E-6 | | -4.05E-2 | 3.78E-14 | 1.44E-8 | | | 7.31E-7 | |
| NOx | -4.34E-6 | | 3.45E-3 | -1.08E-13 | 1.43E-4 | 8.28E-8 | | 8.91E-5 | 1.2E+0 |
| PM-10 | -4.34E-6 | | 3.45E-3 | -1.08E-13 | 5.42E-4 | | | 3.75E-4 | 9.6E-2 |
| (NM)VOC | 1.14E-5 | | -1.21E-1 | 1.39E-13 | | 7.63E-6 | | 6.46E-7 | 4.3E-2 |
| SOx | -1.23E-5 | | 9.80E-3 | -3.06E-13 | 3.72E-4 | | | 5.46E-5 | 3.1E-1 |
| 1,3-Butadiene | 1.43E-5 | | -1.26E-1 | 1.39E-13 | 8.66E-5 | 1.25E-5 | 1.58E-5 | 1.87E-6 | 2.2E+3 |
| Formaldehyde | 1.43E-5 | | -5.18E-1 | 1.39E-13 | 5.34E-5 | 7.10E-7 | 9.91E-7 | 1.11E-6 | 8.3E-1 |
| Toluene | 1.14E-5 | | -1.21E-1 | 1.39E-13 | | 5.56E-6 | | 1.36E-6 | 3.3E-1 |
| Benzene | 1.43E-5 | | -1.31E-1 | 1.39E-13 | 2.11E-5 | 3.94E-6 | 2.50E-6 | 4.68E-7 | 1.9E+3 |
| Acetaldehyde | 1.14E-5 | | -1.21E-1 | 1.39E-13 | | 6.63E-6 | 2.16E-7 | 1.36E-6 | 4.3E-2 |
| Methane | 3.19E-5 | 4.40E-6 | -9.45E-2 | 3.09E-13 | | 8.73E-8 | | 1.28E-8 | |
| MTBE | 1.14E-5 | | -1.21E-1 | 1.39E-13 | | 3.60E-6 | | 3.32E-7 | 4.3E-2 |
| DPM-10 | -4.34E-6 | | 3.45E-3 | -1.08E-13 | 6.80E-1 | | 9.78E-6 | 7.00E-4 | 5.7E+5 |

(1) All EPS, Eco-Indicator damage factors are the "raw" factors, without normalization or application of weighting factors.
(2) Shaded cells indicate the stressor is not assigned to the impact category; i.e., the cell (indictor) value is zero.
(3) EPS values from Steen (1999a). Calculated disability-adjusted life-years (CDALYs) calculated based on 1 YOLL = 1 CDALY, 1 person-year severe morbidity = 0.7 CDALY, 1 person-year morbidity = 0.4 CDALY, 1 person-year severe nuisance = 0.1 CDALY, and 1 person-year nuisance = 0.05 CDALY. EPS productive capacity calculated as the (unweighted) sum of crop, wood, and fish/meat productive capacity loss indicators.
(4) Eco-Indicator values from Goedkoop and Spriensma (2000a), based on Egalitarian perspective.
(5) USES-LCA toxicity potentials from Huijbregts, et a.(2000).
(6) EPS values for (NM)VOC based on p-xylene. EPS values for MTBE based on dimethylether.
(7) Diesel particulate matter values: EPS values for polyaromatic compounds use for human health effects, PM-10 values used for other effects. USES-LCA values based on "carcinogenic PAHs." Eco-Indicator values based on "diesel soot" for carcinogenic effects and PM-2.5 for other effects.
(8) USES-LCA values for (NM)VOC, acetaldehyde and MTBE estimated based upon p-xylene.
(9) EPS damage factors for $NO_x$, $SO_x$, PM-10 and DPM-10 for above impact categories are calculated from pathway-specific characterization factors provided by Steen (1999a), as the reported, summed values combine certain damages (factors) across the above impact categories.
(10) All values based on emissions to air (as initial compartment). All values in units per kg stressor.

**Table 3. LCIA Damage Function Indicators by Impact Category (cont.)**

| **Stressor** | **Impact Category and Indicator Type and Value** | | | | | |
|---|---|---|---|---|---|---|
| | Eco-Toxicity | | | | | |
| | USES-LCA (FW Aq. Toxicity) | USES-LCA (Mar. Aq. Toxicity) | USES-LCA (FW Sed. Toxicity) | USES-LCA (Mar. Sed. Toxicity) | USES-LCA (Terrestrial Toxicity) | Eco-Indicator PDF (Pot. Disapp. Fract.) |
| $CO_2$ | | | | | | |
| CO | | | | | | |
| NOx | | | | | | |
| PM-10 | | | | | | |
| (NM)VOC | 6.1E-5 | 6.1E-4 | 3.7E-5 | 3.8E-4 | 5.3E-7 | |
| SOx | | | | | | |
| 1,3-Butadiene | 3.3E-7 | 2.7E-6 | 2.2E-7 | 3.0E-6 | 2.3E-8 | |
| Formaldehyde | 8.3E+0 | 1.6E+0 | 4.5E+0 | 1.5E+0 | 9.4E-1 | |
| Toluene | 7.0E-5 | 7.0E-4 | 5.0E-5 | 5.8E-4 | 1.6E-5 | 2.40E-4 |
| Benzene | 8.5E-5 | 2.8E-3 | 6.4E-5 | 1.3E-3 | 1.6E-5 | 2.75E-3 |
| Acetaldehyde | 6.1E-5 | 6.1E-4 | 3.7E-5 | 3.8E-4 | 5.3E-7 | |
| Methane | | | | | | |
| MTBE | 6.1E-5 | 6.1E-4 | 3.7E-5 | 3.8E-4 | 5.3E-7 | |
| DPM-10 | 1.7E+2 | 4.3E+3 | 5.6E+2 | 1.4E+4 | 1.0E+0 | 7.80E-4 |

| | Oxidant Formation | Acidification | | | N-Nutrification | Eutrophication | Acid. + Eutroph. |
|---|---|---|---|---|---|---|---|
| | EPS–Prod. Cap. | EPS–Base Cat.Cap. | EPS–Prod. Cap. | EPS – NEX | EPS–Prod. Cap. | EPS - NEX | Eco-Indicator PDF |
| $CO_2$ | | | | | | | |
| CO | | | | | | | |
| NOx | 0.706 | 1.09 | | | -2.77 | 1.83E-13 | 5.713 |
| PM-10 | | | | | | | |
| (NM)VOC | 2.97 | | | | | | |
| SOx | | 1.56 | 1.18E-3 | 1.18E-14 | | | 1.041 |
| 1,3-Butadiene | 4.86 | | | | | | |
| Formaldehyde | 2.06 | | | | | | |
| Toluene | 2.17 | | | | | | |
| Benzene | 1.54 | | | | | | |
| Acetaldehyde | 2.59 | | | | | | |
| Methane | 0.034 | | | | | | |
| MTBE | 1.40 | | | | | | |
| DPM-10 | | | | | | | |

**Table 4. Normalized Values of $b_{Xlijk}$ Used in Evaluation of Human Health and Ecological Potential Damage, $u_{HD}$(HD) and $u_{ED}$(ED)**

| | **Human Health Damage Category** | | | | | | **Ecological Damage Category** | |
|---|---|---|---|---|---|---|---|---|
| | GLOBAL WARMING | | HUMAN TOXICITY | | OXIDANT FORMATION | | SPECIES LOSS | |
| Stressor | EPS-CDALY | Eco-In. DALY | EPS-CDALY | Eco-In. DALY | EPS-CDALY | Eco-In. DALY | EPS-NEX | Eco-In. PDF |
| $CO_2$ | (.38, .55, .78) | (.31, .45, .67) | | | | | (1, 1, 1) | (0, 0, 0) |
| CO | (1, 1, 1) | (0, 0, 0) | (.38, .55, .78) | (.31, .45, .67) | | | (1, 1, 1) | (0, 0, 0) |
| $NO_x$ | (1, 1, 1) | (0, 0, 0) | (.40, .58, .90) | (.27, .42, .60) | (1, 1, 1) | (0, 0, 0) | (.43, .64, 1.0) | (.21, .36, .56) |
| PM-10 | (1, 1, 1) | (0, 0, 0) | (.40, .58, .90) | (.27, .42, .60) | | | (1, 1, 1) | (0, 0, 0) |
| (NM)VOC | (1, 1, 1) | (0, 0, 0) | | | (.33, .50, .75) | (.33, .50, .75) | (1, 1, 1) | (0, 0, 0) |
| $SO_x$ | (1, 1, 1) | (0, 0, 0) | (.40, .58, .90) | (.27, .42, .60) | | | (.43, .64, 1.0) | (.21, .36, .56) |
| 1,3-Butadiene | (1, 1, 1) | (0, 0, 0) | (.21, .36, .56) | (.43, .64, 1.0) | (.21, .36, .56) | (.43, .64, 1.0) | (1, 1, 1) | (0, 0, 0) |
| Formaldehyde | (1, 1, 1) | (0, 0, 0) | (.21, .36, .56) | (.43, .64, 1.0) | (.21, .36, .56) | (.43, .64, 1.0) | (1, 1, 1) | (0, 0, 0) |
| Toluene | (1, 1, 1) | (0, 0, 0) | | | (.21, .36, .56) | (.43, .64, 1.0) | (.40, .58, .90) | (.27, .42, .60) |
| Benzene | (1, 1, 1) | (0, 0, 0) | (.31, .45, .67) | (.38, ,55, .78) | (.31, .45, .67) | (.38, ,55, .78) | (.40, .58, .90) | (.27, .42, .60) |
| Acetaldehyde | (1, 1, 1) | (0, 0, 0) | (0, 0, 0) | (1, 1, 1) | (.31, .45, .67) | (.38, ,55, .78) | (1, 1, 1) | (0, 0, 0) |
| CH4 | (.38, .55, .78) | (.31, .45, .67) | | | (.40, .58, .90) | (.27, .42, .60) | (1, 1, 1) | (0, 0, 0) |
| MTBE | (1, 1, 1) | (0, 0, 0) | | | (.21, .36, .56) | (.43, .64, 1.0) | (1, 1, 1) | (0, 0, 0) |
| DPM-10 | (1, 1, 1) | (0, 0, 0) | (.43, .64, 1.0) | (.21, .36, .56) | (0, 0, 0) | (1, 1, 1) | (.45, .67, 1.17) | (.09, .33, .67) |

| Table 5. Unit Partial Utility Factors Used in Simulation | | | | |
|---|---|---|---|---|
| Veh. Type | Utility Factor | Per Mile | Per Minute Engine Idling | Per Engine Start |
| 1 | $u_{HD}$(HD) | -(2.665E-6, 3.970E-6, 5.800E-6) | -(4.405E-7, 6.393E-7, 9.230E-7) | -(4.210E-7, 6.258E-7, 9.053E-7) |
| | $u_{ED}$(ED) | -(3.833E-6, 4.300E-6, 4.918E-6) | -(7.463E-7, 8.228E-7, 9.245E-7) | -(7.168E-7, 8.763E-7, 1.090E-6) |
| | $u_{HP}$(HP) | -(1.523E-6, 4.370E-6, 1.476E-5) | -(6.258E-7, 1.795E-6, 8.753E-6) | -(4.015E-7, 1.152E-6, 5.063E-6) |
| | $u_{EP}$(EP) | -(1.767E-6, 5.693E-6, 1.774E-5) | -(3.853E-7, 1.242E-6, 5.993E-6) | -(2.575E-7, 8.295E-7, 4.330E-6) |
| | $u_R$(R) | -8.320E-06 | -8.955E-07 | -6.133E-07 |
| | $u_O$(O) | -8.630E-06 | -9.105E-08 | -6.250E-08 |
| 2 | $u_{HD}$(HD) | -(3.243E-6, 4.833E-6, 7.050E-6) | -(1.822E-7, 2.753E-7, 3.995E-7) | -(1.235E-7, 1.865E-7, 2.708E-7) |
| | $u_{ED}$(ED) | -(5.210E-6, 5.913E-6, 6.843E-6) | -(2.461E-7, 3.023E-7, 3.775E-7) | -(1.686E-7, 2.070E-7, 2.583E-7) |
| | $u_{HP}$(HP) | -(1.899E-6, 5.448E-6, 1.784E-5) | -(8.180E-8, 2.347E-7, 6.928E-7) | -(5.613E-8, 1.610E-7, 4.750E-7) |
| | $u_{EP}$(EP) | -(2.239E-6, 7.215E-6, 2.230E-5) | -(9.038E-8, 2.913E-7, 1.042E-6) | -(6.215E-8, 2.002E-7, 7.140E-7) |
| | $u_R$(R) | -8.215E-06 | -6.783E-08 | -4.710E-08 |
| | $u_O$(O) | -9.155E-06 | -7.143E-09 | -3.573E-09 |
| 3 | $u_{HD}$(HD) | -(4.038E-6, 6.018E-6, 8.778E-6) | -(7.898E-7, 1.143E-6, 1.649E-6) | -(9.730E-7, 1.460E-6, 2.100E-6) |
| | $u_{ED}$(ED) | -(5.960E-6, 6.880E-6, 8.038E-6) | -(1.343E-6, 1.473E-6, 1.647E-6) | -(1.695E-6, 2.232E-6, 2.95E-6) |
| | $u_{HP}$(HP) | -(2.421E-6, 6.948E-6, 2.389E-5) | -(1.260E-6, 3.615E-6, 1.736E-5) | -(9.505E-7, 2.728E-6, 1.296E-5) |
| | $u_{EP}$(EP) | -(2.665E-6, 8.590E-6, 2.808E-5) | -(7.933E-7, 2.558E-6, 1.222E-5) | -(3.758E-7, 1.211E-6, 1.062E-5) |
| | $u_R$(R) | -1.164E-05 | -1.601E-06 | -7.168E-07 |
| | $u_O$(O) | -8.273E-06 | -2.788E-07 | -7.323E-08 |
| 4 | $u_{HD}$(HD) | -(2.179E-5, 3.218E-5, 4.915E-5) | -(7.058E-6, 1.035E-5, 1.600E-5) | -(4.910E-6, 7.188E-6, 1.105E-5) |
| | $u_{ED}$(ED) | -(6.688E-6, 8.505E-6, 1.093E-5) | -(5.578E-7, 6.973E-7, 8.885E-7) | -(5.768E-7, 6.730E-7, 8.015E-7) |
| | $u_{HP}$(HP) | -(1.293E-5, 3.710E-5, 8.068E-5) | -(4.368E-6, 1.253E-5, 2.583E-5) | -(3.768E-6, 1.081E-5, 3.230E-5) |
| | $u_{EP}$(EP) | -(6.210E-6, 2.001E-5, 7.015E-5) | -(1.845E-6, 5.943E-6, 1.871E-5) | -(1.344E-6, 4.333E-6, 1.949E-5) |
| | $u_R$(R) | -7.630E-06 | -1.053E-06 | -7.153E-07 |
| | $u_O$(O) | -8.953E-06 | -9.825E-08 | -6.608E-08 |

**Table 6. Values of Selected Simulation and Experimental Parameters**

**SIMULATION PARAMETERS**

| Request-Related Parameters: | Value |
|---|---|
| Trip distance (miles) | Exp (9.4) |
| Requested pick-up time | Normal (13:00, 5:00) |
| Call-in time offset (hrs.) | Exp (2.4) |
| Wheelchair patron loading/unloading time (hours) | Uniform (0.1, 0.25) |
| Non-wheelchair patron loading/unloading time (hours) | Uniform (0.0075, 0.01 |
| Probability (p) of wheelchair request | 0.2 |

| Schedule and Penalty Parameters: | Value |
|---|---|
| Early pick-up window (all requests, min.) | 5 |
| Late pick-up window—advance requests (min.) | 15 |
| Late pick-up window—immediate service requests (min.) | 60 |
| Lateness after which VERY LATE penalty applies (min.) | 60 |
| Earliness penalty ($/min.) | 0.1 |
| Lateness penalty ($/min.) | 0.5 |
| Flat-rate very late penalty ($) | 100 |
| Planned ride time factor | 1.5 |
| Maximum ride time factor | 2.5 |

Vehicle Cost and Capacity Parameters:

| Vehicle Type | Sym. | $/mile | WhChr. Cap. | Non-WhChr. Cap. |
|---|---|---|---|---|
| Gasoline “minivan” | GV | 0.375 | 1 | 3 |
| CNG “minivan” | CV | 0.449 | 1 | 3 |
| Gasoline “shuttle bus” | GB | 0.445 | 2 | 5 |
| Diesel “shuttle bus” | DB | 0.413 | 2 | 5 |

Shift Schedules:

| Shift | Start | End | Shift | Start | End |
|---|---|---|---|---|---|
| 1 | 00:00 | 08:00 | 4 | 12:00 | 20:00 |
| 2 | 04:00 | 12:00 | 5 | 16:00 | 24:00 |
| 3 | 08:00 | 16:00 | 6 | 20:00 | 04:00 |

**EXPERIMENTAL PARAMETERS**

Vehicle Shift Assignments:

| Case | Tot. Veh. Sim. | Sh1 | Sh2 | Sh3 | Sh4 | Sh5 | Sh6 |
|---|---|---|---|---|---|---|---|
| A | 150 | 11 | 28 | 40 | 39 | 22 | 10 |
| B | 180 | 13 | 34 | 48 | 47 | 26 | 12 |
| C | 210 | 15 | 40 | 55 | 55 | 30 | 15 |

Fleet Composition:

| Case | GV | CV | GB | DB | Case | GV | CV | GB | DB |
|---|---|---|---|---|---|---|---|---|---|
| IA | 39 | 39 | 36 | 36 | IC | 55 | 55 | 55 | 55 |
| IB | 47 | 47 | 43 | 43 | | | | | |
| IIA | | 75 | 75 | | IIC | | 105 | 105 | |
| IIB | | 90 | 90 | | | | | | |
| IIIA | | | 150 | | IIIC | | | 210 | |
| IIIB | | | 180 | | | | | | |

Objective Function Environmental Weight ($w_{ENV}$):

Values: 0, 0.125, 0.25, 0.50, 0.75

| Table 7. Comparison of Service Performance Results for Simulated Cases | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Fleet Size (Tot. Veh.) | $W_{env}$ | Requests Served | Rideshare | Mean P/U Delay (min.) | Std. Dev. | Overall O/T Perf. | Std. Dev. | Vehicle Utilization |
| Case I – Heterogeneous Fleet (CV, GV, GB, DB) (n = 10, 1000 requests/day) | | | | | | | | |
| 210 | **0** | **9998** | **1.36** | **31.12** | **1.19** | **0.763** | **0.01** | **0.682** |
| | .125 | 10000 | 1.37 | 32.73 | 1.12 | 0.748 | 0.01 | 0.674 |
| | .25 | 9998 | 1.37 | 34.01 | 1.94 | 0.733 | 0.02 | 0.664 |
| | .5 | 9999 | 1.37 | 40.38 | 1.97 | 0.688 | 0.02 | 0.660 |
| | .75 | 10000 | 1.34 | 49.00 | 2.74 | 0.649 | 0.01 | 0.667 |
| 180 | **0** | **9968** | **1.37** | **32.47** | **1.49** | **0.754** | **0.02** | **0.782** |
| | .125 | 9976 | 1.38 | 33.48 | 1.16 | 0.742 | 0.01 | 0.777 |
| | .25 | 9974 | 1.38 | 35.98 | 1.43 | 0.715 | 0.02 | 0.769 |
| | .5 | 9979 | 1.37 | 43.51 | 2.43 | 0.672 | 0.02 | 0.758 |
| | .75 | 9955 | 1.35 | 52.54 | 2.71 | 0.625 | 0.02 | 0.772 |
| 150 | **0** | **9727** | **1.38** | **42.84** | **2.80** | **0.686** | **0.02** | **0.877** |
| | .125 | 9717 | 1.39 | 43.04 | 2.32 | 0.680 | 0.01 | 0.873 |
| | .25 | 9731 | 1.39 | 43.33 | 1.73 | 0.677 | 0.01 | 0.867 |
| | .5 | 9650 | 1.38 | 51.79 | 2.29 | 0.624 | 0.02 | 0.870 |
| | .75 | 9474 | 1.34 | 61.27 | 2.71 | 0.594 | 0.01 | 0.869 |
| Case II – Heterogeneous Fleet (CV, GB) (n = 10, 1000 requests/day) | | | | | | | | |
| 210 | **0** | **9998** | **1.36** | **30.88** | **1.06** | **0.771** | **0.02** | **0.687** |
| | .125 | 9999 | 1.35 | 31.60 | 0.77 | 0.761 | 0.01 | 0.686 |
| | .25 | 9999 | 1.35 | 32.88 | 1.10 | 0.747 | 0.01 | 0.682 |
| | .5 | 9998 | 1.36 | 36.70 | 1.53 | 0.712 | 0.02 | 0.668 |
| | .75 | 9999 | 1.34 | 46.60 | 1.97 | 0.657 | 0.01 | 0.677 |
| 180 | **0** | **9972** | **1.37** | **32.60** | **2.05** | **0.757** | **0.01** | **0.785** |
| | .125 | 9968 | 1.35 | 33.28 | 1.25 | 0.746 | 0.01 | 0.785 |
| | .25 | 9976 | 1.37 | 34.34 | 1.31 | 0.735 | 0.02 | 0.783 |
| | .5 | 9970 | 1.36 | 38.21 | 1.70 | 0.704 | 0.01 | 0.774 |
| | .75 | 9957 | 1.35 | 48.09 | 2.17 | 0.655 | 0.01 | 0.780 |
| 150 | **0** | **9699** | **1.37** | **41.90** | **3.03** | **0.696** | **0.02** | **0.877** |
| | .125 | 9718 | 1.38 | 42.83 | 2.28 | 0.685 | 0.02 | 0.876 |
| | .25 | 9703 | 1.37 | 43.49 | 1.81 | 0.679 | 0.01 | 0.876 |
| | .5 | 9660 | 1.37 | 46.69 | 2.28 | 0.655 | 0.01 | 0.869 |
| | .75 | 9446 | 1.34 | 56.58 | 1.54 | 0.613 | 0.01 | 0.874 |
| Case III – Homogeneous Fleet (GB) (n = 10, 1000 requests/day) | | | | | | | | |
| 210 | **0** | **9996** | **1.36** | **30.81** | **1.26** | **0.773** | **0.01** | **0.688** |
| | .125 | 9999 | 1.36 | 31.71 | 0.69 | 0.761 | 0.01 | 0.684 |
| | .25 | 9999 | 1.37 | 32.56 | 1.03 | 0.749 | 0.02 | 0.683 |
| | .5 | 9997 | 1.36 | 35.93 | 1.13 | 0.729 | 0.01 | 0.675 |
| | .75 | 9997 | 1.35 | 44.08 | 1.63 | 0.675 | 0.02 | 0.689 |
| 180 | **0** | **9970** | **1.37** | **32.40** | **1.42** | **0.757** | **0.02** | **0.784** |
| | .125 | 9966 | 1.37 | 33.55 | 0.95 | 0.744 | 0.01 | 0.780 |
| | .25 | 9978 | 1.37 | 34.23 | 0.96 | 0.739 | 0.01 | 0.779 |
| | .5 | 9970 | 1.36 | 37.52 | 1.66 | 0.717 | 0.01 | 0.777 |
| | .75 | 9943 | 1.35 | 45.87 | 2.09 | 0.670 | 0.02 | 0.792 |
| 150 | **0** | **9733** | **1.40** | **42.26** | **2.80** | **0.694** | **0.02** | **0.877** |
| | .125 | 9738 | 1.39 | 42.64 | 2.39 | 0.684 | 0.03 | 0.877 |
| | .25 | 9728 | 1.40 | 43.43 | 2.42 | 0.681 | 0.02 | 0.876 |
| | .5 | 9678 | 1.38 | 46.74 | 2.12 | 0.658 | 0.02 | 0.872 |
| | .75 | 9424 | 1.33 | 56.64 | 1.52 | 0.615 | 0.01 | 0.879 |

1) "Baseline case" results (without environmental scheduling algorithm) shown in boldface.
2) Ridesharing is calculated as the total number of requests served divided by the number of trip starts.
3) Mean pick-up delay calculated as actual time service began minus requested pick-up time. "Negative" delays (vehicle arrives early) are assigned a delay value of zero.
4) Overall on-time performance = fraction of pick-ups where vehicle arrived early or within the "on time" window.
5) Vehicle utilization = the total number of hours vehicles were in transit (with or without passengers on-board) plus total loading/unloading times divided by the total number of available vehicle hours.

**Table 8. Scheduling Algorithm Results—Cost and Environmental Performance**

| Fleet Size (Tot. Veh.) | $W_{env}$ | Average Distance | Avg. Itin. Cost ($) | Std. Dev. | u(Cost) | Std. Dev. | u(Env.) | Std. Dev. | u(System) |
|---|---|---|---|---|---|---|---|---|---|
| Case I – Heterogeneous Fleet (CV, GV, GB, DB) (n = 10, 1000 requests/day) | | | | | | | | | |
| 210 | **0** | **29626.2** | **15157.72** | **416.28** | **-0.2010** | **0.0056** | **-0.4671** | **0.0075** | **-0.2010** |
| | .125 | 29252.0 | 15796.81 | 447.54 | -0.2096 | 0.0060 | -0.3159 | 0.0168 | -0.2228 |
| | .25 | 28774.0 | 16617.17 | 631.21 | -0.2204 | 0.0085 | -0.2965 | 0.0082 | -0.2394 |
| | .5 | 28549.6 | 20084.79 | 983.20 | -0.2666 | 0.0131 | -0.2827 | 0.0102 | -0.2747 |
| | .75 | 28910.0 | 25556.68 | 1519.62 | -0.3395 | 0.0203 | -0.2884 | 0.0090 | -0.3011 |
| 180 | **0** | **29061.3** | **15659.72** | **690.72** | **-0.2078** | **0.0092** | **-0.4378** | **0.0053** | **-0.2078** |
| | .125 | 28878.8 | 16180.12 | 602.38 | -0.2147 | 0.0081 | -0.3622 | 0.0126 | -0.2331 |
| | .25 | 28523.4 | 17245.32 | 872.21 | -0.2289 | 0.0117 | -0.3462 | 0.0131 | -0.2582 |
| | .5 | 28095.2 | 21721.36 | 1214.64 | -0.2884 | 0.0163 | -0.3232 | 0.0093 | -0.3058 |
| | .75 | 28657.7 | 27425.69 | 1319.89 | -0.3644 | 0.0176 | -0.3374 | 0.0104 | -0.3441 |
| 150 | **0** | **27080.4** | **20418.81** | **1434.68** | **-0.2715** | **0.0191** | **-0.3980** | **0.0064** | **-0.2715** |
| | .125 | 26960.9 | 20332.97 | 897.77 | -0.2703 | 0.0120 | -0.3665 | 0.0044 | -0.2823 |
| | .25 | 26753.6 | 20582.79 | 829.29 | -0.2736 | 0.0111 | -0.3589 | 0.0070 | -0.2949 |
| | .5 | 26867.0 | 24983.19 | 1271.53 | -0.3321 | 0.0170 | -0.3559 | 0.0090 | -0.3440 |
| | .75 | 26913.9 | 29922.99 | 1269.21 | -0.3981 | 0.0170 | -0.3541 | 0.0072 | -0.3651 |
| Case II – Heterogeneous Fleet (CV, GB) (n = 10, 1000 requests/day) | | | | | | | | | |
| 210 | **0** | **29838.3** | **16225.27** | **520.43** | **-0.2153** | **0.0069** | **-0.2987** | **0.0056** | **-0.2153** |
| | .125 | 29795.5 | 16566.07 | 437.63 | -0.2197 | 0.0059 | -0.2817 | 0.0068 | -0.2274 |
| | .25 | 29614.4 | 17196.09 | 412.02 | -0.2281 | 0.0054 | -0.2793 | 0.0079 | -0.2409 |
| | .5 | 28959.7 | 19302.05 | 753.74 | -0.2562 | 0.0101 | -0.2716 | 0.0054 | -0.2639 |
| | .75 | 29386.7 | 25481.85 | 1149.79 | -0.3386 | 0.0154 | -0.2752 | 0.0066 | -0.2911 |
| 180 | **0** | **29188.7** | **16819.80** | **757.82** | **-0.2232** | **0.0102** | **-0.2880** | **0.0049** | **-0.2232** |
| | .125 | 29190.3 | 17230.37 | 676.94 | -0.2286 | 0.0091 | -0.2800 | 0.0045 | -0.2351 |
| | .25 | 29107.5 | 17731.01 | 618.03 | -0.2352 | 0.0084 | -0.2789 | 0.0050 | -0.2461 |
| | .5 | 28752.1 | 19981.29 | 895.22 | -0.2652 | 0.0120 | -0.2744 | 0.0039 | -0.2698 |
| | .75 | 28999.0 | 25832.82 | 1113.36 | -0.3434 | 0.0149 | -0.2765 | 0.0060 | -0.2932 |
| 150 | **0** | **27090.1** | **20698.34** | **1557.70** | **-0.2752** | **0.0208** | **-0.2643** | **0.0033** | **-0.2752** |
| | .125 | 27061.6 | 21188.18 | 1348.96 | -0.2817 | 0.0179 | -0.2609 | 0.0025 | -0.2791 |
| | .25 | 27062.7 | 21532.41 | 896.29 | -0.2862 | 0.0120 | -0.2608 | 0.0036 | -0.2798 |
| | .5 | 26852.6 | 23527.71 | 1128.79 | -0.3128 | 0.0151 | -0.2583 | 0.0029 | -0.2855 |
| | .75 | 27065.5 | 28846.22 | 866.60 | -0.3838 | 0.0115 | -0.2600 | 0.0030 | -0.2910 |
| Case III – Homogeneous Fleet (GB) (n = 10, 1000 requests/day) | | | | | | | | | |
| 210 | **0** | **29904.2** | **16266.48** | **550.57** | **-0.2159** | **0.0074** | **-0.3228** | **0.0094** | **-0.2159** |
| | .125 | 29695.1 | 16550.16 | 315.66 | -0.2196 | 0.0043 | -0.3204 | 0.0078 | -0.2322 |
| | .25 | 29668.5 | 17295.16 | 501.07 | -0.2293 | 0.0068 | -0.3201 | 0.0073 | -0.2520 |
| | .5 | 29271.0 | 19432.14 | 731.37 | -0.2578 | 0.0097 | -0.3156 | 0.0081 | -0.2867 |
| | .75 | 29925.5 | 24983.88 | 831.03 | -0.3318 | 0.0112 | -0.3229 | 0.0078 | -0.3251 |
| 180 | **0** | **29142.9** | **16601.94** | **488.41** | **-0.2204** | **0.0066** | **-0.3141** | **0.0050** | **-0.2204** |
| | .125 | 28977.7 | 17080.74 | 628.31 | -0.2266 | 0.0083 | -0.3122 | 0.0047 | -0.2373 |
| | .25 | 28954.6 | 17724.38 | 525.52 | -0.2351 | 0.0071 | -0.3120 | 0.0051 | -0.2543 |
| | .5 | 28869.7 | 19930.39 | 1009.47 | -0.2645 | 0.0135 | -0.3110 | 0.0038 | -0.2878 |
| | .75 | 29462.5 | 25553.31 | 1118.42 | -0.3395 | 0.0150 | -0.3177 | 0.0054 | -0.3231 |
| 150 | **0** | **27105.0** | **20976.28** | **1260.17** | **-0.2789** | **0.0168** | **-0.2911** | **0.0029** | **-0.2789** |
| | .125 | 27096.7 | 21171.14 | 1181.05 | -0.2815 | 0.0157 | -0.2910 | 0.0031 | -0.2827 |
| | .25 | 27047.1 | 21702.76 | 989.87 | -0.2884 | 0.0132 | -0.2905 | 0.0034 | -0.2889 |
| | .5 | 26952.3 | 23692.69 | 1101.36 | -0.3150 | 0.0146 | -0.2894 | 0.0040 | -0.3022 |
| | .75 | 27262.3 | 28909.33 | 1178.80 | -0.3846 | 0.0157 | -0.2928 | 0.0049 | -0.3158 |

| Table 9. Comparison of Results Affecting Environmental Performance | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fleet Size | $W_{env}$ | Avg. Vehicles Utilized | | | | Average Distance | Std. Dev. | Engine Starts | Std. Dev. | Waiting[(1)] Idle (hrs.) | Std. Dev. |
| | | GV | CV | GB | DB | | | | | | |
| Case I – Heterogeneous Fleet (CV, GV, GB, DB) (n = 10, 1000 requests/day) | | | | | | | | | | | |
| 210 | **0** | **55.0** | **31.3** | **46.1** | **49.7** | **29626.2** | **602.5** | **420.4** | **19.6** | **2.15** | **0.56** |
| | .125 | 55.0 | 54.7 | 45.3 | 21.6 | 29252.0 | 494.5 | 406.0 | 14.9 | 2.09 | 0.41 |
| | .25 | 55.0 | 54.8 | 44.7 | 16.9 | 28774.0 | 345.1 | 398.7 | 7.9 | 2.61 | 0.72 |
| | .5 | 55.0 | 54.5 | 42.9 | 13.7 | 28549.6 | 280.9 | 381.6 | 14.7 | 2.32 | 0.82 |
| | .75 | 55.0 | 54.3 | 42.8 | 14.5 | 28910.0 | 331.2 | 378.0 | 16.3 | 2.44 | 0.94 |
| 180 | **0** | **47.0** | **40.8** | **41.5** | **43.0** | **29061.3** | **416.3** | **397.7** | **10.8** | **2.14** | **0.82** |
| | .125 | 47.0 | 47.0 | 41.5 | 33.7 | 28878.8 | 425.3 | 389.2 | 12.0 | 2.11 | 0.90 |
| | .25 | 47.0 | 47.0 | 41.4 | 31.2 | 28523.4 | 431.0 | 384.8 | 9.0 | 2.32 | 0.75 |
| | .5 | 47.0 | 47.0 | 41.1 | 25.9 | 28095.2 | 374.1 | 372.9 | 12.1 | 1.94 | 0.40 |
| | .75 | 47.0 | 47.0 | 40.2 | 28.1 | 28657.7 | 488.3 | 368.2 | 11.2 | 1.74 | 0.63 |
| 150 | **0** | **39.0** | **37.0** | **35.7** | **36.0** | **27080.4** | **368.0** | **333.5** | **5.1** | **1.44** | **0.52** |
| | .125 | 39.0 | 39.0 | 35.7 | 33.4 | 26960.9 | 231.7 | 336.0 | 11.0 | 1.54 | 0.59 |
| | .25 | 39.0 | 39.0 | 35.7 | 33.1 | 26753.6 | 247.9 | 332.1 | 10.2 | 2.34 | 1.61 |
| | .5 | 39.0 | 39.0 | 35.7 | 31.7 | 26867.0 | 296.9 | 328.3 | 8.7 | 2.15 | 0.93 |
| | .75 | 39.0 | 39.0 | 35.1 | 31.5 | 26913.9 | 256.2 | 320.0 | 10.7 | 1.48 | 0.77 |
| Case II – Heterogeneous Fleet (CV, GB) (n = 10, 1000 requests/day) | | | | | | | | | | | |
| 210 | **0** | | **78.6** | **104.9** | | **29838.3** | **606.9** | **422.2** | **16.9** | **1.94** | **0.43** |
| | .125 | | 105.0 | 77.8 | | 29795.5 | 587.5 | 425.8 | 18.4 | 2.44 | 0.43 |
| | .25 | | 105.0 | 74.8 | | 29614.4 | 685.6 | 414.0 | 19.9 | 2.31 | 0.79 |
| | .5 | | 104.9 | 67.7 | | 28959.7 | 490.7 | 398.9 | 7.9 | 2.03 | 0.29 |
| | .75 | | 104.9 | 65.4 | | 29386.7 | 587.0 | 386.3 | 14.1 | 2.11 | 0.53 |
| 180 | **0** | | **82.8** | **90.0** | | **29188.7** | **516.2** | **398.4** | **12.4** | **1.98** | **0.53** |
| | .125 | | 90.0 | 82.9 | | 29190.3 | 413.2 | 401.3 | 9.5 | 1.89 | 0.36 |
| | .25 | | 90.0 | 82.3 | | 29107.5 | 477.8 | 399.2 | 9.7 | 2.32 | 0.95 |
| | .5 | | 90.0 | 78.2 | | 28752.1 | 363.2 | 385.6 | 10.6 | 2.26 | 0.86 |
| | .75 | | 89.9 | 75.5 | | 28999.0 | 561.1 | 370.6 | 11.0 | 2.02 | 0.64 |
| 150 | **0** | | **73.0** | **75.0** | | **27090.1** | **342.7** | **335.5** | **9.6** | **1.85** | **0.68** |
| | .125 | | 75.0 | 73.1 | | 27061.6 | 227.1 | 336.4 | 9.5 | 1.78 | 0.74 |
| | .25 | | 75.0 | 73.1 | | 27062.7 | 335.6 | 334.8 | 9.1 | 1.97 | 0.85 |
| | .5 | | 75.0 | 71.6 | | 26852.6 | 274.9 | 334.5 | 4.8 | 2.15 | 0.84 |
| | .75 | | 75.0 | 70.2 | | 27065.5 | 288.5 | 322.7 | 6.4 | 1.49 | 0.56 |
| Case III – Homogeneous Fleet (GB) (n = 10, 1000 requests/day) | | | | | | | | | | | |
| 210 | **0** | | | **183.8** | | **29904.2** | **832.8** | **425.6** | **15.7** | **2.24** | **0.75** |
| | .125 | | | 183.4 | | 29695.1 | 692.3 | 421.3 | 15.7 | 2.20 | 0.46 |
| | .25 | | | 181.5 | | 29668.5 | 648.6 | 420.3 | 15.5 | 2.44 | 0.78 |
| | .5 | | | 176.8 | | 29271.0 | 721.0 | 406.7 | 15.5 | 2.42 | 0.63 |
| | .75 | | | 178.2 | | 29925.5 | 689.8 | 401.1 | 13.0 | 2.01 | 0.66 |
| 180 | **0** | | | **173.1** | | **29142.9** | **447.2** | **396.6** | **11.9** | **2.01** | **0.66** |
| | .125 | | | 172.7 | | 28977.7 | 417.7 | 397.1 | 12.0 | 2.32 | 0.55 |
| | .25 | | | 172.3 | | 28954.6 | 457.0 | 400.7 | 9.0 | 2.02 | 0.45 |
| | .5 | | | 171.0 | | 28869.7 | 340.0 | 393.3 | 7.2 | 2.42 | 0.82 |
| | .75 | | | 170.6 | | 29462.5 | 478.2 | 382.7 | 10.5 | 2.05 | 0.70 |
| 150 | **0** | | | **148.1** | | **27105.0** | **262.7** | **334.5** | **4.4** | **1.71** | **0.49** |
| | .125 | | | 148.4 | | 27096.7 | 277.1 | 332.2 | 6.5 | 1.81 | 0.61 |
| | .25 | | | 148.1 | | 27047.1 | 303.5 | 334.7 | 7.6 | 1.99 | 0.59 |
| | .5 | | | 147.7 | | 26952.3 | 356.5 | 335.3 | 6.2 | 1.74 | 0.52 |
| | .75 | | | 146.6 | | 27262.3 | 442.1 | 324.6 | 8.1 | 1.99 | 0.71 |

(1) Engine idling includes only that during waiting and not that during passenger loading/unloading, as the former is controllable and a function of vehicle itinerary whereas the latter is not.

**Table 10a. Scheduling Algorithm Results--Life-Cycle Criteria and Other Pollutant Air Emissions**

| Fleet Size (Tot. Veh.) | $W_{env}$ | VOC (kg) | Air Toxics (kg)[(1)] | SOx (kg) | NOx (kg) | CO (kg) | CO2-Equiv. (kg/1000) | CH4 (kg) | PM10 (kg) | DPM10 (kg) |
|---|---|---|---|---|---|---|---|---|---|---|
| Case I – Heterogeneous Fleet (CV, GV, GB, DB) (n = 10, 1000 requests/day) | | | | | | | | | | |
| 210 | **0** | **19.84** | **1.24** | **32.26** | **73.05** | **103.66** | **28.91** | **26.38** | **4.38** | **0.53** |
| | .125 | 17.00 | 0.93 | 31.04 | 54.76 | 105.74 | 29.03 | 62.34 | 4.51 | 0.16 |
| | .25 | 16.46 | 0.88 | 30.51 | 52.07 | 104.68 | 28.62 | 63.09 | 4.46 | 0.12 |
| | .5 | 16.09 | 0.85 | 30.21 | 50.11 | 103.86 | 28.38 | 64.65 | 4.44 | 0.09 |
| | .75 | 16.32 | 0.86 | 30.58 | 50.93 | 104.77 | 28.69 | 65.24 | 4.48 | 0.10 |
| 180 | **0** | **19.21** | **1.18** | **31.35** | **69.85** | **101.48** | **28.49** | **38.58** | **4.32** | **0.47** |
| | .125 | 17.81 | 1.02 | 30.75 | 60.79 | 102.84 | 28.58 | 56.48 | 4.39 | 0.28 |
| | .25 | 17.38 | 0.99 | 30.37 | 58.65 | 102.41 | 28.31 | 56.87 | 4.35 | 0.25 |
| | .5 | 16.79 | 0.94 | 29.89 | 55.54 | 102.00 | 27.99 | 57.90 | 4.32 | 0.20 |
| | .75 | 17.24 | 0.97 | 30.46 | 57.47 | 102.82 | 28.41 | 58.55 | 4.38 | 0.23 |
| 150 | **0** | **17.83** | **1.09** | **29.10** | **64.55** | **94.96** | **26.71** | **41.87** | **4.04** | **0.41** |
| | .125 | 17.22 | 1.02 | 28.80 | 60.70 | 95.34 | 26.69 | 49.03 | 4.06 | 0.34 |
| | .25 | 17.00 | 1.01 | 28.57 | 59.65 | 94.82 | 26.50 | 49.38 | 4.04 | 0.32 |
| | .5 | 16.99 | 1.00 | 28.69 | 59.31 | 95.60 | 26.64 | 49.76 | 4.06 | 0.31 |
| | .75 | 16.96 | 0.99 | 28.72 | 59.05 | 95.50 | 26.65 | 50.29 | 4.07 | 0.31 |
| Case II – Heterogeneous Fleet (CV, GB) (n = 10, 1000 requests/day) | | | | | | | | | | |
| 210 | **0** | **18.42** | **1.29** | **32.89** | **60.22** | **146.23** | **34.87** | **72.73** | **5.16** | **0.00** |
| | .125 | 17.69 | 1.00 | 30.64 | 56.36 | 118.14 | 31.89 | 124.50 | 4.82 | 0.00 |
| | .25 | 17.55 | 0.98 | 30.37 | 55.87 | 116.38 | 31.59 | 125.65 | 4.78 | 0.00 |
| | .5 | 17.11 | 0.94 | 29.54 | 54.35 | 111.71 | 30.68 | 126.63 | 4.65 | 0.00 |
| | .75 | 17.34 | 0.95 | 29.91 | 55.03 | 112.45 | 31.04 | 130.13 | 4.71 | 0.00 |
| 180 | **0** | **17.84** | **1.19** | **31.65** | **57.99** | **136.34** | **33.42** | **83.46** | **4.97** | **0.00** |
| | .125 | 17.51 | 1.06 | 30.59 | 56.19 | 123.01 | 32.01 | 108.40 | 4.81 | 0.00 |
| | .25 | 17.45 | 1.05 | 30.47 | 55.96 | 122.12 | 31.86 | 109.08 | 4.79 | 0.00 |
| | .5 | 17.20 | 1.02 | 29.97 | 55.07 | 119.09 | 31.31 | 110.57 | 4.71 | 0.00 |
| | .75 | 17.32 | 1.02 | 30.18 | 55.45 | 119.45 | 31.52 | 112.66 | 4.75 | 0.00 |
| 150 | **0** | **16.46** | **1.07** | **29.10** | **53.33** | **122.88** | **30.64** | **83.98** | **4.57** | **0.00** |
| | .125 | 16.32 | 1.01 | 28.65 | 52.56 | 117.50 | 30.05 | 93.75 | 4.50 | 0.00 |
| | .25 | 16.31 | 1.01 | 28.63 | 52.54 | 117.32 | 30.04 | 94.11 | 4.50 | 0.00 |
| | .5 | 16.17 | 1.00 | 28.36 | 52.04 | 115.73 | 29.73 | 94.69 | 4.46 | 0.00 |
| | .75 | 16.28 | 1.00 | 28.53 | 52.35 | 115.93 | 29.89 | 96.67 | 4.48 | 0.00 |
| Case III – Homogeneous Fleet (GB) (n = 10, 1000 requests/day) | | | | | | | | | | |
| 210 | **0** | **19.48** | **1.70** | **36.01** | **65.69** | **185.92** | **39.01** | **0.95** | **5.63** | **0.00** |
| | .125 | 19.34 | 1.69 | 35.76 | 65.23 | 184.61 | 38.74 | 0.94 | 5.59 | 0.00 |
| | .25 | 19.32 | 1.69 | 35.73 | 65.17 | 184.45 | 38.71 | 0.94 | 5.58 | 0.00 |
| | .5 | 19.06 | 1.67 | 35.25 | 64.29 | 181.92 | 38.19 | 0.93 | 5.51 | 0.00 |
| | .75 | 19.48 | 1.70 | 36.03 | 65.70 | 185.82 | 39.04 | 0.95 | 5.63 | 0.00 |
| 180 | **0** | **18.97** | **1.66** | **35.09** | **63.99** | **181.04** | **38.02** | **0.92** | **5.48** | **0.00** |
| | .125 | 18.87 | 1.65 | 34.89 | 63.63 | 180.05 | 37.80 | 0.92 | 5.45 | 0.00 |
| | .25 | 18.85 | 1.65 | 34.86 | 63.59 | 179.94 | 37.78 | 0.92 | 5.45 | 0.00 |
| | .5 | 18.79 | 1.64 | 34.76 | 63.39 | 179.36 | 37.66 | 0.92 | 5.43 | 0.00 |
| | .75 | 19.17 | 1.67 | 35.47 | 64.67 | 182.84 | 38.43 | 0.93 | 5.54 | 0.00 |
| 150 | **0** | **17.63** | **1.54** | **32.64** | **59.47** | **168.10** | **35.36** | **0.86** | **5.10** | **0.00** |
| | .125 | 17.62 | 1.54 | 32.63 | 59.45 | 168.03 | 35.35 | 0.86 | 5.10 | 0.00 |
| | .25 | 17.59 | 1.53 | 32.57 | 59.35 | 167.75 | 35.28 | 0.86 | 5.09 | 0.00 |
| | .5 | 17.53 | 1.53 | 32.45 | 59.14 | 167.17 | 35.16 | 0.85 | 5.07 | 0.00 |
| | .75 | 17.72 | 1.54 | 32.82 | 59.80 | 168.92 | 35.56 | 0.86 | 5.13 | 0.00 |

(1) Includes formaldehyde, 1,4-butadiene, acetaldehyde, toluene, benzene, and MTBE

| Table 10b. Scheduling Algorithm Results—Other Life-Cycle Impacts | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Fleet Size (Tot. Veh.) | $W_{env}$ | TRI/ SARA Emis. (kg) | RCRA Waste Gen. (kg) | Solid Waste Gen. (kg) | Energy Cons. (MJ/1000) | Fuel Cons. (gal.)[1] | Base Metal Cons. (kg) | Prec. Metal Cons. (kg) |
| Case I – Heterogeneous Fleet (CV, GV, GB, DB) (n = 10, 1000 requests/day) | | | | | | | | |
| 210 | **0** | **1.22** | **43.37** | **165.55** | **254.27** | **1631.70** | **1941.55** | **369.91** |
| | .125 | 1.22 | 43.37 | 155.65 | 252.29 | 1657.60 | 1946.92 | 371.03 |
| | .25 | 1.20 | 42.70 | 152.15 | 248.90 | 1639.80 | 1916.23 | 365.17 |
| | .5 | 1.19 | 42.40 | 150.22 | 246.56 | 1627.20 | 1903.72 | 362.80 |
| | .75 | 1.21 | 42.93 | 152.24 | 248.99 | 1642.50 | 1928.26 | 367.49 |
| 180 | **0** | **1.20** | **42.68** | **162.14** | **248.85** | **1600.80** | **1914.29** | **364.75** |
| | .125 | 1.20 | 42.69 | 157.24 | 248.27 | 1616.40 | 1916.80 | 365.27 |
| | .25 | 1.18 | 42.20 | 154.53 | 246.25 | 1607.00 | 1893.40 | 360.80 |
| | .5 | 1.17 | 41.61 | 150.99 | 243.82 | 1597.00 | 1865.77 | 355.53 |
| | .75 | 1.19 | 42.42 | 154.53 | 246.88 | 1613.80 | 1904.40 | 362.91 |
| 150 | **0** | **1.12** | **39.84** | **151.10** | **232.90** | **1500.30** | **1786.83** | **340.46** |
| | .125 | 1.12 | 39.78 | 148.82 | 232.12 | 1503.10 | 1785.03 | 340.14 |
| | .25 | 1.11 | 39.49 | 147.38 | 230.43 | 1493.40 | 1771.94 | 337.64 |
| | .5 | 1.11 | 39.66 | 147.66 | 231.91 | 1504.90 | 1779.24 | 339.03 |
| | .75 | 1.11 | 39.74 | 147.76 | 231.80 | 1504.20 | 1783.35 | 339.82 |
| Case II – Heterogeneous Fleet (CV, GB) (n = 10, 1000 requests/day) | | | | | | | | |
| 210 | **0** | **1.27** | **44.16** | **150.66** | **217.45** | **1433.50** | **2028.78** | **387.27** |
| | .125 | 1.26 | 44.02 | 150.09 | 216.88 | 1430.00 | 2022.00 | 385.97 |
| | .25 | 1.26 | 44.00 | 150.02 | 216.80 | 1429.40 | 2021.14 | 385.80 |
| | .5 | 1.25 | 43.53 | 148.23 | 214.74 | 1416.10 | 1998.90 | 381.56 |
| | .75 | 1.24 | 43.33 | 147.25 | 214.14 | 1413.00 | 1988.62 | 379.59 |
| 180 | **0** | **1.25** | **43.57** | **149.75** | **213.02** | **1401.30** | **2005.35** | **382.82** |
| | .125 | 1.25 | 43.48 | 149.39 | 212.72 | 1399.60 | 2001.31 | 382.05 |
| | .25 | 1.25 | 43.49 | 149.38 | 212.81 | 1400.40 | 2001.52 | 382.09 |
| | .5 | 1.23 | 42.85 | 147.03 | 209.92 | 1381.70 | 1971.63 | 376.38 |
| | .75 | 1.25 | 43.39 | 148.76 | 212.66 | 1399.90 | 1995.85 | 381.00 |
| 150 | **0** | **1.16** | **40.43** | **139.53** | **196.95** | **1294.20** | **1862.97** | **355.65** |
| | .125 | 1.17 | 40.55 | 139.93 | 197.51 | 1297.90 | 1868.29 | 356.67 |
| | .25 | 1.17 | 40.56 | 139.98 | 197.62 | 1298.80 | 1869.08 | 356.82 |
| | .5 | 1.16 | 40.23 | 138.76 | 196.02 | 1288.30 | 1853.28 | 353.80 |
| | .75 | 1.16 | 40.46 | 139.47 | 197.31 | 1296.90 | 1863.80 | 355.81 |
| Case III – Homogeneous Fleet (GB) (n = 10, 1000 requests/day) | | | | | | | | |
| 210 | **0** | **1.14** | **43.93** | **155.20** | **393.29** | **2664.60** | **1798.07** | **340.50** |
| | .125 | 1.13 | 43.62 | 154.12 | 390.54 | 2646.10 | 1785.50 | 338.12 |
| | .25 | 1.13 | 43.58 | 153.98 | 390.19 | 2643.70 | 1783.90 | 337.81 |
| | .5 | 1.11 | 42.99 | 151.92 | 384.95 | 2608.30 | 1759.99 | 333.29 |
| | .75 | 1.14 | 43.96 | 155.31 | 393.55 | 2666.40 | 1799.34 | 340.74 |
| 180 | **0** | **1.11** | **42.81** | **151.25** | **383.26** | **2596.70** | **1752.29** | **331.83** |
| | .125 | 1.10 | 42.56 | 150.39 | 381.09 | 2582.10 | 1742.36 | 329.95 |
| | .25 | 1.10 | 42.53 | 150.27 | 380.79 | 2580.00 | 1740.97 | 329.68 |
| | .5 | 1.10 | 42.41 | 149.83 | 379.67 | 2572.30 | 1735.87 | 328.72 |
| | .75 | 1.12 | 43.27 | 152.91 | 387.45 | 2625.10 | 1771.50 | 335.47 |
| 150 | **0** | **1.03** | **39.81** | **140.68** | **356.44** | **2414.90** | **1629.75** | **308.62** |
| | .125 | 1.03 | 39.80 | 140.63 | 356.33 | 2414.20 | 1629.24 | 308.53 |
| | .25 | 1.03 | 39.73 | 140.37 | 355.68 | 2409.70 | 1626.27 | 307.96 |
| | .5 | 1.02 | 39.59 | 139.88 | 354.43 | 2401.40 | 1620.57 | 306.88 |
| | .75 | 1.04 | 40.04 | 141.49 | 358.49 | 2428.50 | 1639.19 | 310.41 |

(1) Fuel consumption in gasoline-equivalent gallons

| **Table 11. Comparison of Life-Cycle Air Emissions—Percentage Change in Average Daily Emissions Due to New Scheduling Algorithm (Wenv = 0.125) Versus Baseline (Cost-Only Algorithm)** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Fleet Size (Tot. Veh.) | Avg. Cost | VOC) | Air Toxics | SOx | NOx | CO | CO2-Equiv. | CH4 | PM10 | DPM-10 |
| Case I - Heterogeneous Fleet (CV, GV, GB, DB) (n = 10, 1000 requests/day) | | | | | | | | | | |
| 210 | 4.2 | -14.3 | -25.4 | -3.8 | -25.0 | 2.0 | 0.4 | 136.3 | 3.1 | -69.6 |
| 180 | 3.3 | -7.3 | -13.2 | -1.9 | -13.0 | 1.3 | 0.3 | 46.4 | 1.6 | -39.3 |
| 150 | -0.4 | -3.4 | -6.1 | -1.0 | -6.0 | 0.4 | -0.1 | 17.1 | 0.5 | -18.4 |
| Case II - Heterogeneous Fleet (CV, GB) (n = 10, 1000 requests/day) | | | | | | | | | | |
| 210 | 2.1 | -4.0 | -22.4 | -6.8 | -6.4 | -19.2 | -8.5 | 71.2 | -6.5 | |
| 180 | 2.4 | -1.9 | -11.5 | -3.3 | -3.1 | -9.8 | -4.2 | 29.9 | -3.2 | |
| 150 | 2.4 | -0.9 | -5.1 | -1.5 | -1.4 | -4.4 | -1.9 | 11.6 | -1.5 | |
| Case III - Homogeneous Fleet (GB) (n = 10, 1000 requests/day) | | | | | | | | | | |
| 210 | 1.7 | -0.7 | -0.7 | -0.7 | -0.7 | -0.7 | -0.7 | -0.7 | -0.7 | |
| 180 | 2.9 | -0.6 | -0.5 | -0.6 | -0.6 | -0.5 | -0.6 | -0.6 | -0.6 | |
| 150 | 0.9 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | -0.1 | 0.0 | |

## APPENDIX A: VEHICLE LIFE-CYCLE ENVIRONMENTAL IMPACT BASIS

### Life-Cycle Stage Environmental Impacts

Calculated values of life-cycle environmental impacts, by life-cycle stage, are provided in Tables A1 through A4 for the vehicle types considered. The basis for the values is provided in the subsequent "Notes."

**Table A1. Paratransit Life-Cycle Inventory Model and Impact Data Basis (Vehicle Type: Gasoline-Powered, Light Duty Minivan)**

| L/C Stage | Impact | Running (1) | Idle (g/min.) | Start (g/start) |
|---|---|---|---|---|
| Vehicle Operation | Vehicle emissions: | (g/mile) | (g/minute) | (g/start) |
| | NMOG (VOC) (2) | 0.0535 | 0.2746 | 0.2220 |
| | Methane | 0.0087 | 0.0526 | 0.0160 |
| | Benzene | 0.0021 | 0.0123 | 0.0097 |
| | Toluene | 0.0060 | 0.0352 | 0.0276 |
| | Formaldehyde | 0.0013 | 0.0088 | 0.0067 |
| | 1,3-Butadiene | 0.0003 | 0.0018 | 0.0013 |
| | Acetaldehyde | 0.0003 | 0.0018 | 0.0013 |
| | MTBE | 0.0042 | 0.0176 | 0.0149 |
| | CO | 1.61 | 6.19 | 2.92 |
| | $NO_x$ (as $NO_2$) | 0.19 | 0.103 | 0.35 |
| | $CO_2$ | 427 | 107 | 72.3 |
| | PM-10 | 0.0270 | | |
| | $SO_2$ | 0.006 | | |
| | Fuel Consumption: | (gal./mile) | (gal./min.) | (gal./start) |
| | Gasoline | 0.0498 | 0.0125 | 0.0085 |
| Service and Maintenance (inc. fueling) | Fueling: | (g/mile) | (g/minute) | (g/start) |
| | NMOG (VOC) emissions | 0.0100 | 0.0025 | 0.0017 |
| | EIO-LCA Impacts: (3) | Based on vehicle mileage only. | | |
| | Non.renew. energy use | 0.585 | MJ/mile (1MJ = 1E+06 J) | |
| | Ozone-depl. emissions | 0 | kg CFC-equivalents/mile | |
| | Global warm. emissions | 40.0 | g $CO_2$-equivalents/mile | |
| | $SO_2$ emissions | 0.134 | g/mile | |
| | CO emissions | 0.174 | g/mile | |
| | $NO_2$ emissions | 0.096 | g/mile | |
| | VOC emissions | 0.026 | g/mile | |
| | Pb emissions | 0 | g/mile | |
| | PM-10 emissions | 0.013 | g/mile | |
| | TRI air emissions | 0.004 | g/mile (CMU Equiv. Tox. units) | |
| | RCRA wastes | 0.149 | g/mile | |
| | Base-metal ore depletion | 7.21 | g/mile | |
| | Prec. metal ore depletion | 1.35 | g/mile | |

(1) Vehicle use-phase "running" emissions from California Air Resources Board (CARB) EMFAC2000/Burden emissions model as well as from other literature sources. Emissions based on CARB's Unified Correction Cycle to the FTP driving cycle, which is based on average driving speed of approximately 28 mph and includes approximately 6.5 starts/day. See "Notes" for additional details.
(2) NMOG excludes benzene, toluene, formaldehyde, acetaldehyde, 1,3-butadiene, an MTBE.
(3) From Carnegie-Mellon EIO-LCA database as well as literature sources.

| **Table A1. Paratransit Life-Cycle Inventory Model and Impact Data Basis (cont.) (Vehicle Type: Gasoline-Powered, Light Duty Minivan)** | | | | |
|---|---|---|---|---|
| L/C Stage | Impact | Running (g/mi) | Idle (g/min.) | Start (g/start) |
| Fuel Production | EIO-LCA Impacts: (3) | Based on fuel consumption. | | |
| | Non-renew. energy use | 3.913 MJ/mile | 0.982 MJ/min | 0.668 MJ/start |
| | Ozone-depl. emissions | 0 | 0 | 0 |
| | Global warm. emissions ($CO_2$-equivalents) | 187.2 (g/mile) | 47.0 (g/min.) | 32.0 (g/min.) |
| | $SO_2$ emissions | 0.269 | 0.068 | 0.046 |
| | CO emissions | 0.230 | 0.058 | 0.039 |
| | $NO_2$ emissions | 0.341 | 0.086 | 0.058 |
| | VOC emissions | 0.107 | 0.027 | 0.018 |
| | Pb emissions | 0 | 0 | 0 |
| | PM-10 emissions | 0.035 | 0.009 | 0.006 |
| | TRI air emissions | 0.002 | ≈ 0 | ≈ 0 |
| | RCRA wastes | 0.204 | 0.051 | 0.035 |
| | Base-metal ore depletion | 2.072 | 0.520 | 0.354 |
| | Prec. metal ore depletion | 0.304 | 0.076 | 0.052 |
| Vehicle Production | EIO-LCA Impacts: (3) | Based on vehicle mileage only. | | |
| | Non-renew. energy use | 2.99 | MJ/mile | |
| | Ozone-depl. emissions | 0 | kg CFC-equivalents/mile | |
| | Global warm. emissions | 213 | g $CO_2$-equivalents/mile | |
| | $SO_2$ emissions | 0.674 | g/mile | |
| | CO emissions | 1.011 | g/mile | |
| | $NO_2$ emissions | 0.461 | g/mile | |
| | VOC emissions | 0.248 | g/mile | |
| | Pb emissions | 0 | g/mile | |
| | PM-10 emissions | 0.073 | g/mile | |
| | TRI air emissions | 0.036 | g/mile | |
| | RCRA wastes | 1.113 | g/mile | |
| | Base-metal ore depletion | 57.4 | g/mile | |
| | Prec. metal ore depletion | 11.07 | g/mile | |
| Vehicle Disposal | Non-recov. wastes: (4) | Based on vehicle mileage only. | | |
| | Landfilled wastes | 4.80 | g/mile | |
| (4) Landfilled wastes are the only disposal impact modeled. Over 75% of the mass of the vehicle is assumed to be recycled, which consumes energy and materials and generates material "credits"—materials returned to the economy. However, differences among vehicle types and routing/scheduling alternatives based on them are assumed negligible. | | | | |

| Table A2. Paratransit Life-Cycle Inventory Model and Impact Data Basis (Vehicle Type: Gasoline-Powered, Medium Duty "Shuttle Bus") | | | | |
|---|---|---|---|---|
| L/C Stage | Impact | Running (1) | Idle (g/min.) | Start (g/start) |
| Vehicle Operation | Vehicle emissions: | (g/mile) | (g/minute) | (g/start) |
| | NMOG (VOC) (2) | 0.1931 | 0.4665 | 0.5256 |
| | Methane | 0.0310 | 0.0749 | 0.0370 |
| | Benzene | 0.0085 | 0.0205 | 0.0237 |
| | Toluene | 0.0243 | 0.0587 | 0.0674 |
| | Formaldehyde | 0.0060 | 0.1450 | 0.0168 |
| | 1,3-Butadiene | 0.0012 | 0.0029 | 0.0034 |
| | Acetaldehyde | 0.0012 | 0.0029 | 0.0034 |
| | MTBE | 0.0128 | 0.0309 | 0.0337 |
| | CO | 4.596 | 12.3 | 9.198 |
| | $NO_x$ (as $NO_2$) | 1.007 | 0.170 | 1.314 |
| | $CO_2$ | 743.8 | 187.0 | 83.88 |
| | PM-10 | 0.051 | | |
| | $SO_2$ | 0.011 | | |
| | Fuel Consumption: | (gal./mile) | (gal./min.) | (gal./start) |
| | Gasoline | 0.0889 | 0.0223 | 0.0100 |
| Service and Maintenance (inc. fueling) | Fueling: | (g/mile) | (g/minute) | (g/start) |
| | NMOG (VOC) emissions | 0.0178 | 0.0044 | 0.0020 |
| | EIO-LCA Impacts: (3) | Based on vehicle mileage only. | | |
| | Non.renew. energy use | 0.585 | MJ/mile (1MJ = 1E+06 J) | |
| | Ozone-depl. emissions | 0 | kg CFC-equivalents/mile | |
| | Global warm. emissions | 40.0 | g $CO_2$-equivalents/mile | |
| | $SO_2$ emissions | 0.134 | g/mile | |
| | CO emissions | 0.174 | g/mile | |
| | $NO_2$ emissions | 0.096 | g/mile | |
| | VOC emissions | 0.026 | g/mile | |
| | Pb emissions | 0 | g/mile | |
| | PM-10 emissions | 0.013 | g/mile | |
| | TRI air emissions | 0.004 | g/mile (CMU Equiv. Tox. units) | |
| | RCRA wastes | 0.149 | g/mile | |
| | Base-metal ore depletion | 7.21 | g/mile | |
| | Prec. metal ore depletion | 1.35 | g/mile | |

(1) Vehicle use-phase "running" emissions from California Air Resources Board (CARB) EMFAC2000/Burden emissions model as well as from other literature sources. Emissions based on CARB's Unified Correction Cycle to the FTP driving cycle, which is based on average driving speed of approximately 28 mph and includes approximately 6.5 starts/day. See "Notes" for additional details.
(2) NMOG excludes benzene, toluene, formaldehyde, acetaldehyde, 1,3-butadiene, an MTBE.
(3) From Carnegie-Mellon EIO-LCA database as well as literature sources.

| Table A2. Paratransit Life-Cycle Inventory Model and Impact Data Basis (cont.) (Vehicle Type: Gasoline-Powered, Medium Duty "Shuttle Bus") | | | | |
|---|---|---|---|---|
| L/C Stage | Impact | Running (g/mi.) | Idle (g/min.) | Start (g/start) |
| Fuel Production | EIO-LCA Impacts: (3) | Based on fuel consumption. | | |
| | Non-renew. energy use | 9.99 MJ/mile | 1.76 MJ/min. | 0.786 MJ/start |
| | Ozone-depl. emissions | 0 | 0 | 0 |
| | Global warm. emissions | 335.5 | 84.3 | 37.7 |
| | $SO_2$ emissions | 0.481 | 0.121 | 0.054 |
| | CO emissions | 0.411 | 0.103 | 0.046 |
| | $NO_2$ emissions | 0.611 | 0.153 | 0.069 |
| | VOC emissions | 0.192 | 0.048 | 0.021 |
| | Pb emissions | 0 | 0 | 0 |
| | PM-10 emissions | 0.062 | 0.016 | 0.007 |
| | TRI air emissions | 0.003 | 0.001 | ≈ 0 |
| | RCRA wastes | 0.365 | 0.092 | 0.041 |
| | Base-metal ore depletion | 3.699 | 0.929 | 0.415 |
| | Prec. metal ore depletion | 0.545 | 0.137 | 0.061 |
| Vehicle Production | EIO-LCA Impacts: (3) | Based on vehicle mileage only. | | |
| | Non-renew. energy use | 2.56 | MJ/mile | |
| | Ozone-depl. emissions | 0 | kg CFC-equivalents/mile | |
| | Global warm. emissions | 182.8 | g $CO_2$-equivalents/mile | |
| | $SO_2$ emissions | 0.577 | g/mile | |
| | CO emissions | 0.867 | g/mile | |
| | $NO_2$ emissions | 0.462 | g/mile | |
| | VOC emissions | 0.213 | g/mile | |
| | Pb emissions | 0 | g/mile | |
| | PM-10 emissions | 0.062 | g/mile | |
| | TRI air emissions | 0.031 | g/mile | |
| | RCRA wastes | 0.954 | g/mile | |
| | Base-metal ore depletion | 49.21 | g/mile | |
| | Prec. metal ore depletion | 9.49 | g/mile | |
| Vehicle Disposal | Non-recov. wastes: (4) | Based on vehicle mileage only. | | |
| | Landfilled wastes | 5.19 | g/mile | |
| (4) Landfilled wastes are the only disposal impact modeled. Over 75% of the mass of the vehicle is assumed to be recycled, which consumes energy and materials and generates material "credits"—materials returned to the economy. However, differences among vehicle types and routing/scheduling alternatives based on them are assumed negligible. | | | | |

| Table A3. Paratransit Life-Cycle Inventory Model and Impact Data Basis (Vehicle Type: CNG-Powered, Light-Duty Minivan) | | | | |
|---|---|---|---|---|
| L/C Stage | Impact | Running (1) | Idle (g/min.) | Start (g/start) |
| Vehicle Operation | Vehicle emissions: | (g/mile) | (g/minute) | (g/start) |
| | NMOG (VOC) (2) | 0.18 | 0.012 | 0.0082 |
| | Methane | 6.50 | 0.358 | 0.245 |
| | Benzene | | | |
| | Toluene | | | |
| | Formaldehyde | 0.018 | 0.0099 | 0.0068 |
| | 1,3-Butadiene | | | |
| | Acetaldehyde | 0.002 | 0.0001 | 0.0001 |
| | MTBE | | | |
| | CO | 1.20 | 0.032 | 0.0219 |
| | $NO_x$ (as $NO_2$) | 0.75 | 0.139 | 0.0952 |
| | $CO_2$ | 510 | 29 | 19.9 |
| | PM-10 | 0.0256 | 0.022 | 0.0151 |
| | $SO_2$ | | | |
| | Fuel Consumption: | (gal./mile) | (gal./min.) | (gal./start) |
| | CNG (in gallons) | 0.2 | 0.0044 | 0.0030 |
| Service and Maintenance (inc. fueling) | Fueling: | (g/mile) | (g/minute) | (g/start) |
| | CNG emissions (as $CH_4$) | 0.04 | 0.0009 | 0.0006 |
| | EIO-LCA Impacts: (3) | Based on vehicle mileage only. | | |
| | Non.renew. energy use | 0.724 | MJ/mile (1MJ = 1E+06 J) | |
| | Ozone-depl. emissions | 0 | kg CFC-equivalents/mile | |
| | Global warm. emissions | 50 | g $CO_2$-equivalents/mile | |
| | $SO_2$ emissions | 0.266 | g/mile | |
| | CO emissions | 0.215 | g/mile | |
| | $NO_2$ emissions | 0.119 | g/mile | |
| | VOC emissions | 0.032 | g/mile | |
| | Pb emissions | 0 | g/mile | |
| | PM-10 emissions | 0.016 | g/mile | |
| | TRI air emissions | 0.005 | g/mile (CMU Equiv. Tox. units) | |
| | RCRA wastes | 0.184 | g/mile | |
| | Base-metal ore depletion | 8.93 | g/mile | |
| | Prec. metal ore depletion | 1.67 | g/mile | |

(1) Vehicle use-phase "running" emissions from California Air Resources Board (CARB) EMFAC2000/Burden emissions model as well as from other literature sources. Emissions based on CARB's Unified Correction Cycle to the FTP driving cycle, which is based on average driving speed of approximately 28 mph and includes approximately 6.5 starts/day. See "Notes" for additional details.
(2) NMOG excludes benzene, toluene, formaldehyde, acetaldehyde, 1,3-butadiene, an MTBE.
(3) From Carnegie-Mellon EIO-LCA database as well as literature sources.

| Table A3. Paratransit Life-Cycle Inventory Model and Impact Data Basis (cont.) (Vehicle Type: CNG-Powered, Light-Duty Minivan) | | | | |
|---|---|---|---|---|
| L/C Stage | Impact | Running (g/mi.) | Idle (g/min.) | Start (g/start) |
| Fuel Production | EIO-LCA Impacts: (3) | Based on fuel consumption. | | |
| | Non-renew. energy use | 3.14 MJ/mile | 0.069 MJ/min. | 0.047 MJ/start |
| | Ozone-depl. emissions | 0 | 0 | 0 |
| | Global warm. emissions | 150.7 | 3.3 | 2.3 |
| | $SO_2$ emissions | 0.216 | 0.005 | 0.003 |
| | CO emissions | 0.185 | 0.004 | 0.003 |
| | $NO_2$ emissions | 0.275 | 0.006 | 0.004 |
| | VOC emissions | 0.086 | 0.002 | 0.001 |
| | Pb emissions | 0 | 0 | 0 |
| | PM-10 emissions | 0.028 | 0.001 | ≈ 0 |
| | TRI air emissions | 0.001 | ≈ 0 | ≈ 0 |
| | RCRA wastes | 0.164 | 0.004 | 0.002 |
| | Base-metal ore depletion | 1.66 | 0.037 | 0.025 |
| | Prec. metal ore depletion | 0.245 | 0.005 | 0.004 |
| Vehicle Production | EIO-LCA Impacts: (3) | Based on vehicle mileage only. | | |
| | Non-renew. energy use | 3.16 | MJ/mile | |
| | Ozone-depl. emissions | 0 | kg CFC-equivalents/mile | |
| | Global warm. emissions | 225.5 | g $CO_2$-equivalents/mile | |
| | $SO_2$ emissions | 0.712 | g/mile | |
| | CO emissions | 1.069 | g/mile | |
| | $NO_2$ emissions | 0.570 | g/mile | |
| | VOC emissions | 0.262 | g/mile | |
| | Pb emissions | 0 | g/mile | |
| | PM-10 emissions | 0.077 | g/mile | |
| | TRI air emissions | 0.038 | g/mile | |
| | RCRA wastes | 1.177 | g/mile | |
| | Base-metal ore depletion | 60.69 | g/mile | |
| | Prec. metal ore depletion | 11.70 | g/mile | |
| Vehicle Disposal | Non-recov. wastes: (4) | Based on vehicle mileage only. | | |
| | Landfilled wastes | 5.55 | g/mile | |
| (4) Landfilled wastes are the only disposal impact modeled. Over 75% of the mass of the vehicle is assumed to be recycled, which consumes energy and materials and generates material "credits"—materials returned to the economy. However, differences among vehicle types and routing/scheduling alternatives based on them are assumed negligible. | | | | |

| Table A4. Paratransit Life-Cycle Inventory Model and Impact Data Basis (Vehicle Type: Diesel-Powered, [Large] Medium Duty "Shuttle Bus") | | | | |
|---|---|---|---|---|
| L/C Stage | Impact | Running (1) | Idle (g/min.) | Start (g/start) |
| Vehicle Operation | Vehicle emissions: | (g/mile) | (g/minute) | (g/start) |
| | NMOG (VOC) (2) | 0.3443 | 0.1062 | 0.0721 |
| | Methane | 0.0176 | 0.0054 | 0.0037 |
| | Benzene | 0.0021 | 0.0006 | 0.0004 |
| | Toluene | 0.0041 | 0.0013 | 0.0009 |
| | Formaldehyde | 0.0519 | 0.0160 | 0.0109 |
| | 1,3-Butadiene | 0.0021 | 0.0006 | 0.0004 |
| | Acetaldehyde | 0.0104 | 0.0032 | 0.0022 |
| | $SO_2$ | 0.0360 | 0.0111 | 0.0075 |
| | CO | 0.6366 | 0.2695 | 0.1829 |
| | $NO_x$ (as $NO_2$) | 3.6632 | 0.2675 | 0.1816 |
| | $CO_2$ | 444 | 23.6 | 16.0 |
| | PM-10 | 0.0240 | | |
| | DPM-10 | 0.0601 | 0.0230 | 0.0156 |
| | Fuel Consumption: | (gal./mile) | (gal./min.) | (gal./start) |
| | Diesel | 0.0444 | 0.0137 | 0.0093 |
| Service and Maintenance (inc. fueling) | Fueling: | (g/mile) | (g/minute) | (g/start) |
| | NMOG (VOC) emissions | 0.0089 | 0.0028 | 0.0019 |
| | EIO-LCA Impacts: (3) | Based on vehicle mileage only. | | |
| | Non.renew. energy use | 0.668 | MJ/mile (1MJ = 1E+06 J) | |
| | Ozone-depl. emissions | 0 | kg CFC-equivalents/mile | |
| | Global warm. emissions | 46.2 | g $CO_2$-equivalents/mile | |
| | $SO_2$ emissions | 0.153 | g/mile | |
| | CO emissions | 0.199 | g/mile | |
| | $NO_2$ emissions | 0.110 | g/mile | |
| | VOC emissions | 0.299 | g/mile | |
| | Pb emissions | 0 | g/mile | |
| | PM-10 emissions | 0.015 | g/mile | |
| | TRI air emissions | 0.005 | g/mile (CMU Equiv. Tox. units) | |
| | RCRA wastes | 0.170 | g/mile | |
| | Base-metal ore depletion | 8.24 | g/mile | |
| | Prec. metal ore depletion | 1.54 | g/mile | |

(1) Vehicle use-phase "running" emissions from California Air Resources Board (CARB) EMFAC2000/Burden emissions model as well as from other literature sources. Emissions based on CARB's Unified Correction Cycle to the FTP driving cycle, which is based on average driving speed of approximately 28 mph and includes approximately 6.5 starts/day. See "Notes" for additional details.
(2) NMOG excludes benzene, toluene, formaldehyde, acetaldehyde, 1,3-butadiene, an MTBE.
(3) From Carnegie-Mellon EIO-LCA database as well as literature sources.

| Table A4. Paratransit Life-Cycle Inventory Model and Impact Data Basis (cont.) (Vehicle Type: Diesel-Powered, [Large} Medium Duty "Shuttle Bus") | | | | |
|---|---|---|---|---|
| L/C Stage | Impact | Running (g/mi.) | Idle (g/min.) | Start (g/start) |
| Fuel Production | EIO-LCA Impacts: (3) | Based on fuel consumption. | | |
| | Non-renew. energy use | 3.39 MJ/mile | 1.05 MJ/min. | 0.710 MJ/start |
| | Ozone-depl. emissions | 0 | 0 | 0 |
| | Global warm. emissions | 162.8 | 50.2 | 34.1 |
| | $SO_2$ emissions | 0.234 | 0.072 | 0.049 |
| | CO emissions | 0.200 | 0.062 | 0.042 |
| | $NO_2$ emissions | 0.296 | 0.091 | 0.062 |
| | VOC emissions | 0.093 | 0.029 | 0.020 |
| | Pb emissions | 0 | 0 | 0 |
| | PM-10 emissions | 0.030 | 0.009 | 0.006 |
| | TRI air emissions | 0.001 | ≈ 0 | ≈ 0 |
| | RCRA wastes | 0.177 | 0.055 | 0.037 |
| | Base-metal ore depletion | 1.794 | 0.553 | 0.376 |
| | Prec. metal ore depletion | 0.264 | 0.082 | 0.055 |
| Vehicle Production | EIO-LCA Impacts: (3) | Based on vehicle mileage only. | | |
| | Non-renew. energy use | 2.91 | MJ/mile | |
| | Ozone-depl. emissions | 0 | kg CFC-equivalents/mile | |
| | Global warm. emissions | 207.2 | g $CO_2$-equivalents/mile | |
| | $SO_2$ emissions | 0.654 | g/mile | |
| | CO emissions | 0.982 | g/mile | |
| | $NO_2$ emissions | 0.524 | g/mile | |
| | VOC emissions | 0.241 | g/mile | |
| | Pb emissions | 0 | g/mile | |
| | PM-10 emissions | 0.071 | g/mile | |
| | TRI air emissions | 0.096 | g/mile | |
| | RCRA wastes | 1.081 | g/mile | |
| | Base-metal ore depletion | 55.77 | g/mile | |
| | Prec. metal ore depletion | 10.75 | g/mile | |
| Vehicle Disposal | Non-recov. wastes: (4) | Based on vehicle mileage only. | | |
| | Landfilled wastes | 6.82 | g/mile | |
| (4) Landfilled wastes are the only disposal impact modeled. Over 75% of the mass of the vehicle is assumed to be recycled, which consumes energy and materials and generates material "credits"—materials returned to the economy. However, differences among vehicle types and routing/scheduling alternatives based on them are assumed negligible. | | | | |

**Table A5. Combined Life-Cycle Environmental Impacts for Modeled Vehicle Types**

| Impact | LD Gasoline-Powered "Minivan" | | | | LD CNG-Powered "Minivan" | | | | MD Gasoline-Powered "Shuttle Bus" | | | | MD Diesel-Powered "Shuttle Bus" | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | g/mile | g/min. | g/start | g/day | g/mile | g/min. | g/start | g/day | g/mile | g/min. | g/start | g/day | g/mile | g/min. | g/start | g/day |
| Air Emissions: | | | | | | | | | | | | | | | | |
| NMOG (VOC) | 0.4445 | 0.3041 | 0.2417 | | 0.5600 | 0.0140 | 0.0092 | | 0.6419 | 0.5189 | 0.5486 | | 0.9862 | 0.1380 | 0.0940 | |
| Methane | 0.0087 | 0.0526 | 0.0160 | | 6.5400 | 0.3589 | 0.2480 | | 0.0310 | 0.0749 | 0.0370 | | 0.0176 | 0.0054 | 0.0037 | |
| Formaldehyde | 0.0013 | 0.0088 | 0.0067 | | 0.0180 | 0.0099 | 0.0068 | | 0.0060 | 0.1450 | 0.0168 | | 0.0519 | 0.0160 | 0.0109 | |
| 1,3-Butadiene | 0.0003 | 0.0018 | 0.0013 | | | | | | 0.0012 | 0.0029 | 0.0034 | | 0.0021 | 0.0006 | 0.0004 | |
| Acetaldehyde | 0.0003 | 0.0018 | 0.0013 | | 0.0020 | 0.0001 | 0.0001 | | 0.0012 | 0.0029 | 0.0034 | | 0.0104 | 0.0032 | 0.0022 | |
| Toluene | 0.0060 | 0.0352 | 0.0276 | | | | | | 0.0243 | 0.0587 | 0.0674 | | 0.0041 | 0.0013 | 0.0009 | |
| Benzene | 0.0021 | 0.0123 | 0.0097 | | | | | | 0.0085 | 0.0205 | 0.0237 | | 0.0021 | 0.0006 | 0.0004 | |
| Methyl t-Butyl Ether | 0.0042 | 0.0176 | 0.0149 | | | | | | 0.0128 | 0.0309 | 0.0377 | | | | | |
| $SO_x$ ($SO_2$) | 1.083 | 0.068 | 0.046 | | 0.928 | 0.005 | 0.003 | | 1.203 | 0.121 | 0.054 | | 1.077 | 0.083 | 0.057 | |
| $NO_x$ ($NO_2$) | 1.088 | 0.189 | 0.408 | | 1.714 | 0.145 | 0.0992 | | 2.176 | 0.323 | 1.383 | | 4.593 | 0.359 | 0.244 | |
| CO | 3.025 | 6.248 | 2.959 | | 2.669 | 0.036 | 0.0249 | | 6.048 | 12.403 | 9.244 | | 2.018 | 0.332 | 16.042 | |
| GWP ($CO_2$ / $CO_2$-equiv.) | 867.2 | 154.0 | 104.3 | | 936.2 | 32.3 | 22.2 | | 1302.1 | 273.1 | 121.6 | | 860.2 | 73.8 | 50.1 | |
| PM-10 | 0.148 | 0.009 | 0.006 | | 0.1466 | 0.023 | 0.0151 | | 0.188 | 0.016 | 0.007 | | 0.116 | 0.009 | 0.006 | |
| Diesel PM-10 (DPM-10) | | | | | | | | | | | | | 0.0601 | 0.0230 | 0.0156 | |
| TRI air emissions | 0.042 | ≈ 0 | ≈ 0 | | 0.044 | ≈ 0 | ≈ 0 | | 0.038 | 0.001 | ≈ 0 | | 0.041 | ≈ 0 | ≈ 0 | |
| Other Impacts: | | | | | | | | | | | | | | | | |
| Non-renew. energy use | 7.488 | 0.982 | 0.668 | | 7.024 | 0.069 | 0.047 | | 13.135 | 1.760 | 0.786 | | 6.968 | 1.050 | 0.710 | |
| Fuel use (in gasoline eq.)* | 0.0498 | 0.0125 | 0.0086 | | 0.0454 | 0.0010 | 0.0007 | | 0.0889 | 0.0223 | 0.0100 | | 0.0387 | 0.0157 | 0.0107 | |
| Base-metal ore depletion | 66.682 | 0.520 | 0.354 | | 71.280 | 0.037 | 0.025 | | 60.119 | 0.929 | 0.415 | | 65.804 | 0.553 | 0.376 | |
| Prec.-metal ore depletion | 12.724 | 0.076 | 0.052 | | 13.615 | 0.005 | 0.004 | | 11.385 | 0..137 | 0.061 | | 12.554 | 0.082 | 0.055 | |
| RCRA Wastes | 1.466 | 0.051 | 0.035 | | 1.525 | 0.004 | 0.002 | | 1.468 | 0.092 | 0.041 | | 1.428 | 0.055 | 0.037 | |
| Non-recycled solid waste | 4.800 | | | | 5.560 | | | | 5.190 | | | | 6.82 | | | |

* Fuels are considered in terms of gasoline-equivalents. Gallons of No. 2 diesel fuel and CNG (3,000 psi) are converted to gasoline equivalent units based on heat content values reported by MacLean (1998). The conversion factors are: 1 gallon diesel = 1.148 gallons gasoline-equivalent, 1 gallon CNG = 0.227 gallons gasoline-equivalent.

**Environmental Impact Basis and Operating Cost "Notes"**

The following notes pertain to, and provide details concerning, calculation of paratransit life-cycle impacts presented in Tables A1 to A4. Impacts, in particular operating emissions, are intended to be representative of the various types of paratransit vehicles modeled, that is, for generic classes of vehicles as opposed to any specific vehicle models, makes, or years. Moreover, even if specific makes and models of vehicles were considered, operating emissions would be significantly influenced by factors such as mileage, state of maintenance, temperature and humidity, etc. (CARB, 2000). This is to say, while certain impacts (pollutant emissions) were estimated by relatively crude techniques, where literature was not readily available, the accuracy of the estimated values should be viewed in the previous context.

GENERAL

(1) In the paratransit LCI model, for the vehicle operation life-cycle stage, impacts are determined as a function of VMT (travel distance), idling time, and number of engine starts. Impacts for fuel production and distribution are calculated based on fuel consumed, which is calculated for each of the previous activities in the previous determination. Impacts for other life-cycle impacts are attributed only to vehicle operation.

(2) EMFAC/Burden vehicle emissions were modeled for the Los Angeles County vehicle fleet, for calendar year 2001, limited to vehicle model years 1998 through 2000. EMFAC default modeling parameters were used; and annual average emissions were requested. Emission rates were calculated from Burden data by dividing total emissions by total miles or total starts. For the fleet comprised on model years 1998 to 2000, the simulated driving cycle includes about 6.5 starts. (See CARB, 2000, July.) Since the EMFAC/Burden model vehicle activity is based on the fleet average, the total number of vehicle starts is the number of vehicles times 6.5, or the number of trips reported in the Burden results. Thus, the impact "per start" is the Burden total "start" emissions divided by this number.

(3) The EMFAC driving cycle includes brief periods of zero mph or near-zero mph travel; and, emissions from these periods are included in "running" emissions reported by Burden. And, in the paratransit LCI model, they are treated likewise, i.e., as part of "running" or in-transit emissions. The "idling" emission component of vehicle operation in the paratransit LCI model pertains to idling that occurs during passenger boarding and discharging. And, the data used for these emissions were taken primarily from literature sources. (See Note 11.)

(4) For the vehicle fleet and EMFAC run described in Note 2, the Burden results (emissions are in tons/day) for light-duty gasoline powered passenger vehicles (with exhaust catalyst) are:

| | | | |
|---|---|---|---|
| Vehicles: | 732, 403 | Trips: | 4,774,282 |
| VMT/1000: | 29,811 | Gasoline consumed: | 1, 484,000 gallons |

| (tons) | TOG | CO | $NO_x$ | $CO_2$ | PM10 |
|---|---|---|---|---|---|
| Running | 1.95 | 52.8 | 6.38 | 14,010 | 0.21 |
| Start | 1.5 | 15.4 | 1.83 | 380 | 0.01 |
| Hot Soak (evap.) | 0.08 | | | | |
| Running (evap.) | 0.55 | | | | |
| Tire wear | | | | | 0.26 |
| Break wear | | | | | 0.42 |
| Lead | | | | | 0 |
| $SO_x$ | | | | | 0.19 |

(5) In the EMFAC model, fugitive organic emissions (diurnal, hot soak, running, resting) are modeled differently. Diurnal and resting emissions occur when the vehicle is not operating. Hot soak emissions occur within an hour after the vehicle has been turned off. Running emissions are evaporative fuel losses while the vehicle is running.

In the paratransit LCI model, diurnal and resting evaporative emissions are not considered because they are not functions of vehicle scheduling—they occur whether the vehicle has been operated or not. Hot soak emissions occur as a result of engine starts; and, in the LCI model they are attributed on this basis. Running emissions are a function of vehicle activity—primarily VMT, but, also, to a small extent, idling. (See CARB, 2000b; CARB,1996, Oct.) In the paratransit LCI model, they are modeled solely as a function of VMT or distance. While this results in a slight error, it is only the difference in error among routing alternatives that are relevant; and, these differences are assumed to be negligible.

(6) EMFAC/Burden report organic emissions as (user specified) TOG (total organic gases), ROG (reactive organic gasses), THC (total hydrocarbon), and methane (CARB, 2000b). THCs include only C-H compounds and exclude carbonyls. NMHC (non-methane hydrocarbon equivalent) is a term used by USEPA and it includes all non-oxygenated species (including methane) plus the hydrocarbon fraction of oxygenated species including carbonyls. VOCs (volatile organic compounds), a term also in general use, exclude methane and other exempt/non-reactive species. VOC is assumed to be approximately equivalent to NMHC (MacLean, 1998).

From the EMFAC conversion factors, the following THC : TOG : ROG : methane ratios are calculated (for LD, gasoline powered vehicle):

| Running | Starting | Hot Soak/Running | Diurnal/Resting |
|---|---|---|---|
| 1:1.07:0.92:0.14 | 1:1.06:1:0.06 | 1:1.06:1:0.06 | 1:1.12:1.12:0. |

USEPA (2000, July) reports exhaust VOCs for a typical gasoline-powered engine are comprised of the following organic air toxics: acetaldehyde (0.5%), 1,3-butadiene (0.5%), formaldehyde (1%), benzene (4%), and toluene (10%).

## LD GASOLINE-POWERED VEHICLE IMPACTS

(7) TOG emissions are determined, based on EMFAC/Burden data, to be 0.0594 g/mile running exhaust, 0.0168 g/mile running evaporative, 0.285 g/start, and 0.015 g/start (hot soak). The

latter value is an approximation in that it assumes all starts produce hot soak emissions. The total organic exhaust emissions are 0.105 g/mile, including running and start exhaust emissions.

Based on the EMFAC conversion factors, TOG running exhaust emissions are estimated to be comprised of 87% non-methane organic gases (NMOG) and 13% methane. TOG start, hot soak, and running evaporative emissions are estimated to be comprised of 94.5% NMOG and 5.5% methane. Then, by multiplying the previous emissions by these compositions:

| | Running (g/mile) | Start (g/start) |
|---|---|---|
| NMOG | 0.0676 | 0.284 |
| Methane | 0.00865 | 0.016. |

For comparison purposes, total exhaust emissions are calculated as 0.105 g/mile, comprised of approximately 0.094 g/mile NMOG. Black, Tejada, and Gurevich (1998) tested several models of vehicles using reformulated gasoline (RFG) and the FTP test cycle. They report total NMOG emissions on the order of 0.11 to 0.15 g/mile. USDoE (1994) reports methane emissions, based on USEPA's MOBILE5 model, as 0.008 g/mile. Thus, given differences in fuels, vehicles or fleets, test cycles, and other factors, the previously calculated values are seen as reasonable.

(8) NMOG exhaust emissions are further decomposed into constituents of 1,3-butadiene, formaldehyde, benzene, acetaldehyde, and toluene based on experimental data reported by Winebrake and Deaton (1999), Black, et al (1998), as well as from data from USEPA (2000, July) as 1,3-butadiene (0.5%), formaldehyde (2.5%), benzene (3.5%), acetaldehyde (0.5%), and toluene (10%). Additionally, based on Black, et al, exhaust emissions are assumed to be comprised of MTBE (5%).

Evaporative emissions would not be expected to contain combustion products (such as aldehydes), but to more closely resemble the composition of the fuel. (See Black, et al.) Therefore, evaporative NMOG emissions are estimated, using data from Black, et al, as benzene (2%), toluene (5%), and MTBE (10%). The composition of NMOG emissions is assumed to be the same for both running exhaust and start-exhaust emissions. Likewise, the composition of evaporative emissions is assumed to be the same for both running and hot-soak evaporative emissions.

(9) Based on the emissions rates and compositions above, the emissions rates for all species are calculated as:

| | g/mile | g/start |
|---|---|---|
| NMOG-other | 0.0535 | 0.2220 |
| Methane | 0.0087 | 0.0160 |
| Benzene | 0.0021 | 0.0097 |
| Toluene | 0.0060 | 0.0276 |
| Formaldehyde | 0.0013 | 0.0067 |
| 1,3-Butadiene | 0.0003 | 0.0013 |
| Acetaldehyde | 0.0003 | 0.0013 |
| MTBE | 0.0042 | 0.0149 |

The total emissions are 0.0764 g/mile and 0.2295g/start. Importantly, it should be noted that these values, and those calculated for other life-cycle impacts, are intended to be representative rather than specific to a particular vehicle make and model, since a generic vehicle is assumed. Moreover, actual emission rates are a function of vehicle age, mileage, mechanical condition, as well as actual driving conditions. Thus, estimation of these impacts based on a more extensive survey of available data is not warranted.

(10) Emission rates of CO, $NO_x$, $CO_2$, and PM-10 are taken from EMFAC/Burden data (see previous note in "General" section) by dividing the running and start exhaust quantities by the number of miles and starts, respectively. They are found to be:

| | g/mile | g/start | g/mile inc. starts |
|---|---|---|---|
| CO | 1.61 | 2.92 | 2.07 |
| $NO_x$ | 0.19 | 0.35 | 0.25 |
| $CO_2$ | 427 | 72.3 | 438 |
| $SO_x$ | 0.006 | ----- | 0.006. |

A good correlation is found between these values and others reported in the literature. For example, Black, et al, based on actual testing, report $NO_x$ emission rates of 0.15 to 0.29 g/mile and CO emission rates of 1.44 to 3.36 g/mile.

(11) PM-10 emission rates can also be calculated from EMFAC/Burden data. However, start emissions, which are negligible, are excluded. Reported data includes that for brake wear. Based on Armstrong (1994), the particulates from brake wear are assumed to be comprised to 10 percent copper and 0.5 percent zinc. Therefore, the calculated values are:

| | g/mile |
|---|---|
| Cu | 0.0013 |
| Zn | 0.0001 |
| PM-10 (other) | 0.0256 |

(12) Idling emissions for VOC, CO, and $NO_x$ are taken from USEPA (1998, April), as 0.352, 6.19, and 0.103 g/minute, respectively. VOC (NMOG) constituents are (crudely) assumed to be present at the same ratios as running exhaust emissions. Methane emissions are then estimated using the NMOG : methane ratio for running emissions.

(13) Fuel consumption is approximated from EMFAC/Burden data as 20.1 mile/gallon. Idling fuel consumption is assumed to be 0.75 gallons/hour or 0.0125 gallon/minute. Idling $CO_2$ emissions are estimated based on fuel consumption (running). Fuel consumption per start is then estimated based on $CO_2$ (start) emissions.

MEDIUM-DUTY GASOLINE-POWERED VEHICLE ("SHUTTLE BUS") IMPACTS

(14) For the vehicle fleet and EMFAC run described in Note 2, the Burden results (emissions are in tons/day) for medium-duty gasoline powered trucks (with exhaust catalyst) are:

| | | | |
|---|---|---|---|
| Vehicles: | 131,771 | Trips: | 1,299,077 |
| VMT/1000: | 5,860 | Gasoline consumed: | 520,830 gallons |

| (tons) | TOG | CO | $NO_x$ | $CO_2$ | PM10 |
|---|---|---|---|---|---|
| Running | 1.541 | 29.66 | 6.50 | 4880 | 0.07 |
| Start | 0.89 | 0.943 | 13.16 | 120 | 0.01 |
| Hot Soak (evap.) | 0.02 | | | | |
| Running (evap.) | 0.05 | | | | |
| Tire + brake wear | | | | | 0.25 |
| Lead | | | | | 0 |
| $SO_x$ | | | | | 0.07 |

Then, using the same composition (NMOG : methane) and similar calculation as for LD gasoline-powered passenger vehicles (Note 7):

| | Running emissions (g/mile) | Start emissions (g/start)* |
|---|---|---|
| NMOG | 0.216 | 0.637 |
| Methane | 0.031 | 0.037 |

(* Start emissions in g/start calculated by dividing total start plus hot soak emissions by number of vehicle trips.)

(15) NMOG emissions are further decomposed into constituents for running/start and evaporative emissions following the same composition and calculation as for LD gasoline-powered passenger vehicles (see Notes 8 and 9). These emissions are:

| | g/mile | g/start |
|---|---|---|
| NMOG-Other | 0.1931 | 0.5256 |
| Methane | 0.0310 | 0.0370 |
| Benzene | 0.0085 | 0.0237 |
| Toluene | 0.0243 | 0.0674 |
| Formaldehyde | 0.0060 | 0.0168 |
| 1,3-Butadiene | 0.0012 | 0.0034 |
| Acetaldehyde | 0.0012 | 0.0034 |
| MTBE | 0.0128 | 0.0337 |

(16) CO, $NO_x$, $CO_2$, $SO_x$, and PM-10 emissions are taken directly from EMFAC/Burden data (see Note 10):

| | g/mile | g/start |
|---|---|---|
| CO | 4.596 | 9.198 |
| $NO_x$ | 1.007 | 1.314 |
| $CO_2$ | 743.8 | 83.88 |
| $SO_x$ | 0.011 | --- |
| PM-10 | 0.050 | 0.007 |

(17) Idling emissions for VOC (NMOG), CO, and $NO_x$ from USEPA (1998, April) for heavy-duty (>8,500 lbs.) gasoline trucks: VOC (0.597 g/min.), CO (12.3 g/min.), and $NO_x$ (0.170 g/min.). VOC (NMOG) constituents calculated analogously to those for LD gasoline-powered

passenger vehicles. See Note 12. $CO_2$ idling emissions calculated analogously to those for LD gasoline-powered passenger vehicles, based on idling fuel consumption of 0.0223 gal./min. See Note 13. Fuel consumption per start (0.0100 gal./start) estimated based upon $CO_2$ start emissions. See Note 13.

MEDIUM-DUTY DIESEL-POWERED VEHICLE ("SHUTTLE BUS") IMPACTS

(18) Diesel vehicle emission factors consider exhaust emissions only, due to unavailability of data for evaporative emissions. Diesel running exhaust emissions from EMFAC/Burden data (see Note 2) for medium-duty diesel trucks:

| | | | |
|---|---|---|---|
| Vehicles: | 14,392 | Trips: | 122,660 |
| VMT/1000: | 756 | Fuel consumed: | 33,600 gal. |

| (tons) | THC | TOG | CO | $NO_x$ | $CO_2$ | DPM-10 | PM-10 | $SO_x$ |
|---|---|---|---|---|---|---|---|---|
| | 0.25 | 0.36 | 0.53 | 3.05 | 370 | 0.05 | 0.02 | 0.03 |

Diesel particulate emissions (DPM-10) are exhaust emissions; and, these are differentiated from other particulate emissions. PM-10 emissions are due to brakes and tire wear, as reported by EMFAC/Burden.

Diesel emission TOG:THC:methane ratio is from CARB (2000b) and is assumed the same for running, start, and idling exhaust emissions:

$$TOG = 1.4417\ THC, \qquad CH_4 = 0.0408\ TOG.$$

(19) From the above, running exhaust emissions are calculated to be:

| | g/mile | | g/mile |
|---|---|---|---|
| NMOG : | 0.4148 | $CO_2$: | 444 |
| $CH_4$: | 0.0176 | $SO_x$: | 0.0369 |
| CO: | 0.6366 | PM-10: | 0.0240 |
| $NO_x$: | 3.6632 | DPM-10: | 0.0601 |

(20) Diesel exhaust NMOG is assumed to be comprised of the same constituents as gasoline exhaust NMOG, although at different proportions, based on Nylund and Lawson (2000). The composition is assumed to be: benzene (0.5%), toluene (1.0%), formaldehyde (12.5%), 1,3-butadiene (0.5%), and acetaldehyde (2.5%). On this basis, running exhaust emissions are calculated to be:

| | g/mile | | g/mile |
|---|---|---|---|
| NMOG-Other (VOC): | 0.3443 | Formaldehyde: | 0.0519 |
| Methane: | 0.0176 | 1.3-Butadiene: | 0.0021 |
| Benzene: | 0.0021 | Acetaldehyde: | 0.0104 |
| Toluene: | 0.0041 | | |

(21) Diesel vehicle idling emissions are assumed (as mid-point values) based on data reported by USEPA (1998, April) and McCormick, Graboski, Alleman, and Yanowitz (2000). The values used are:

| | g/min. |
|---|---|
| NMOG: | 0.1280 |
| $CH_4$: | 0.0054 |
| CO: | 0.2695 |
| $NO_x$: | 0.2675 |
| DPM-10: | 0.0230 |

(22) Diesel vehicle idling $CO_2$ emissions are calculated as a ratio, based on NMOG emissions, to running emissions to be 23.6 g/min.

(23) Diesel idling fuel consumption is calculated similarly, based on NMOG emissions and calculated running fuel consumption rate (22.5 mpg) as 0.0137 gallon/minute.

(24) Due to lack of reported data, diesel "start" fuel consumption is (crudely) estimated by analogy to LD gasoline vehicle "start" fuel consumption as 0.0093 gallon/start.

(25) Diesel "start" emissions are assumed to be identical in composition to idling emissions and are calculated based on idling emissions and the ratio of start : idling fuel consumption.

LD CNG-POWERED VEHICLE ("MINIVAN") IMPACTS

(26) The following CNG-powered vehicle ("minivan") running emissions are assumed, based on data reported by Deaton and Winebrake (2000) for a fleet of LEV-certified Dodge vans with 5.2 l fuel-injection engines:

| | g/mile | | g/mile |
|---|---|---|---|
| CO | 1.2 | $NO_x$ | 0.75 |
| NMHC | 0.2 | $CO_2$ | 510 |

(27) The following CNG-powered vehicle idling emissions are assumed based on data reported by McCormick, et al (2000) for a fleet of LEV-certified busses with 5.9 l engines:

| | g/minute | | g/minute |
|---|---|---|---|
| CO | 0.032 | NOx | 0.139 |
| THC | 0.369 | PM-10 | 0.022 |

(28) Start and running evaporative emissions are assumed to be zero for CNG-powered vehicles (MacLean, 1998).

(29) Based on data reported by MacLean, CNG hydrocarbon emissions are assumed to be comprised of 97% $CH_4$ and 3% NMOG, where NMOG is comprised of both combustion products as well as the non-methane constituents of unburned fuel. Unburned fuel is (crudely) assumed to constitute 90% of NMOG. According to Carslow and Fricker (1995), CNG (fuel) is comprised of 93% methane and 7% other alkanes (which include

VOCs and non-VOCs). The primary oxygenated combustion products are formaldehyde and acetaldehyde, found at a ratio of 8.75:1 (MacLean).

(30) On the above basis, the hydrocarbon and other CNG-powered vehicle running and idling emissions are assumed to be the values below. The hydrocarbon compositions of running and idling emissions are assumed to be the same. PM-10 running emissions are assumed to be primarily comprised of tire and brake particulates (from EMFAC/Burden results); and, the same value as that for the gasoline-powered LD vehicle (0.0256 g/mile) is assumed. Idling $CO_2$ emissions are estimated using ratios (running:idling THC emissions) and running $CO_2$ emissions.

(31) CNG-vehicle idling fuel consumption is calculated based upon $CO_2$ ratios and running fuel consumption and is calculated to be 0.011 gal. CNG/minute. CNG consumption is based on compressed (3000-3600 psi) natural gas, reported in units of gallons, where one gallon CNG is equal to approximately 0.24 gallons gasoline-equivalent (MacLean).

(32) According to MacLean, starting of CNG-fueled engines does not require fuel enrichment, unlike starting of gasoline-fueled engines. And, CNG engine “start” emissions are then assumed to be of composition identical to running and idling emissions. CNG “start” emissions (and fuel consumption) are estimated using the same idling : start ratio as diesel-fueled engines.

FUEL-CYCLE, SERVICE, AND OTHER LIFE-CYCLE ENVIRONMENTAL IMPACTS—
ALL VEHICLE TYPES

(33) VOC (as NMOG) fueling emissions (for gasoline-fueled vehicles are calculated based upon fuel consumed and emission rates reported by DeLuchi (1993). He reports vehicle fueling emissions ranging from 0.00 to 2.44 grams VOC (NMOG) per gallon consumed, depending upon the vehicle and pumpside emission controls in place. In 59 FR 16262 (April 6, 1994), USEPA published a rule setting the allowable standard at 0.20 grams/gallon of fuel dispensed. This value is used for both gasoline and diesel fuels; and, “per mile,” “per minute (idle),” and “per start” values are calculated using the previously calculated fuel consumptions for each (with the same simplifying assumption used to calculate fuel consumption, namely, EMFAC/Burden fuel mileage is based on running miles only).
For CNG fueling, a loss of one gram per five gallons CNG is assumed, together with the simplifying assumption that the emissions consists entirely of methane.

(34) Environmental impact data for vehicle service and maintenance, petroleum refining, and vehicle production is taken primarily from the EIO-LCA database. As this data is based on economic transactions in producer prices in 1992 dollars, current producer prices (e.g., for gasoline, vehicles) are multiplied by a factor of 0.85 to convert 2000-year dollars to 1992-year dollars. The factor of 0.85 is based on Implicit Price Deflators published by the USDoC Bureau of Economic Analysis. (Alternatively, Producer Price Index factors might have been used.)

The EIO-LCA data (Green Design Initiative, 2000) for $1 million of incremental production is:

| Impact | Unit | Veh. Prod. | Petr. Refining | Auto Service/Maint. | Insurance |
|---|---|---|---|---|---|
| Energy | TJ | 14.247 | 109.1 | 9.278 | 3.732 |
| ODP | mt CFC-eq. | 0 | 0 | 0 | 0 |
| $SO_2$ | mt | 3.208 | 7.509 | 2.124 | 0.773 |
| CO | mt | 4.816 | 6.415 | 2.762 | 1.545 |
| $NO_2$ | mt | 2.569 | 9.533 | 1.527 | 0.623 |
| VOC | mt | 1.182 | 3.000 | 0.415 | 0.420 |
| Pb | mt | 0.003 | 0 | 0.001 | 0 |
| PM-10 | mt | 0.346 | 0.970 | 0.209 | 0.099 |
| GWP | mt $CO_2$-eq. | 1015.7 | 5234. | 641.8 | 252.1 |
| Base metal cons. | mt | 273.4 | 57.7 | 114.5 | 9.94 |
| Prec. metal cons. | mt | 52.7 | 8.5 | 21.4 | 1.9 |
| RCRA waste, shipped | mt | 5.3 | 5.7 | 2.36 | 0.706 |
| TRI air releases | mt | 0.473 | 0.276 | 0.143 | 0.030 |
| TRI air releases, CMU-ET weighted | mt | 0.171 | 0.043 | 0.070 | 0.008 |
| TRI offsite | mt | 1.308 | 0.244 | 0.477 | 0.045 |
| TRI offsite, CMU-ET weighted | mt | 10.348 | 1.069 | 4.58 | 0.387 |

**TRI emissions (quantities) shown in the life-cycle inventories for the vehicle types are based on CMU Equivalent Toxicity rather than actual (unadjusted) values.**

(35) Vehicle service and maintenance costs (excluding fuel) are estimated, based on "popular" data such as that published by the American Automobile Association, to be $6,700 over a 90,000-mile vehicle (LD gasoline-powered "minivan") lifetime. This is approximately $5,700 in 1992-year dollars, or $0.063 1992-year dollars/mile when allocated on a "per mile" basis. Service and maintenance costs for the other vehicles are assumed to be proportional to the vehicles' purchase prices and are allocated over the vehicles expected lifetimes:

| Vehicle Type | Est. Life (miles) | Prod. Price ($1992) | Maint.($1992) | $1992 maint./mile |
|---|---|---|---|---|
| LD Gasoline | 90,000 | $ 16,150 | $ 5,700 | $ 0.063 |
| LD CNG | 90,000 | 19,975 | 7,050 | 0.078 |
| MD Gasoline | 175,000 | 31,450 | 11,100 | 0.063 |
| MD Diesel | 200,000 | 40,800 | 14,400 | 0.072 |

For purposes of determining EIO-LCA-based impacts arising from vehicles service and maintenance, 1992-year dollars are used (Green Design Initiative, 2000). For use in the vehicle scheduling objective function, current-year dollars (2000) are used.

(36) EIO-LCA fuel cycle emissions are based on a 1992-year dollar (producer) price of $0.72/gallon for unleaded gasoline. This corresponds to a current-dollar producer price of approximately $0.85/gallon, which may be compared to current futures prices of between $0.85 and $0.91/galon.

The EIO-LCA-based impacts in grams/mile, due to gasoline production, for VOC, CO, $NO_x$, $SO_x$, and PM-10, respectively, are found to be 0.107, 0.230, 0.341, 0.269, and 0.035 for the LD gasoline-powered vehicle (20.1 miles per gallon). For comparison, DeLuchi (1993) reports these emissions for refineries, including emissions from the generation of purchased electricity.

His values, respectively, are 0.054, 0.095, 0.137, 0.144, and 0.015 when converted to the same per mile basis. The EIO-LCA results are seen as reasonable given the additional sectors included.

EIO-LCA-based impacts due to the production of other fuels (CNG and diesel) are calculated similarly, that is, based upon vehicle fuel economy (mileage) and fuel producer prices ($1992) of:

| | |
|---|---|
| Diesel: $0.70 | CNG: $0.144. |

(For comparison purposes, MacLean reports $1992 retail prices of $1.10 (gasoline), $1.07 (diesel), $0.91 (CNG in gasoline equivalents), and $0.22 (CNG per gallon).

(37) Vehicle production impacts are calculated from EIO-LCA data based on the 1992 $ producer prices in Note 35. Vehicle are also assumed to have no salvage value. Allocated "per mile" (usage or depreciation) costs are calculated by dividing the 1992$ vehicle producer price by the vehicle lifetime (see Note 35). Economic costs (Note 40) are allocated based upon 2000$ purchase price and vehicle lifetime.

(38) Fixed costs are those arising from insurance, licensing, and financing activities; and, the indirect (equilibrium) environmental impacts of these activities are non-trivial (Maclean). Fixed costs are assumed to be equal to 15 percent of the vehicle purchase price (1992$) per year. While there is an intuitive basis for allocating the environmental impacts from the other life-cycle stages—e.g., vehicle and fuel production—on a "per mile" basis, there is no obvious rationale for allocating the environmental impacts of the previous fixed costs on the same basis. Instead, these are allocated on a "daily usage" basis (where 365 potential days of usage per year is assumed). The rationale for this is that if vehicles in the fleet are underutilized, they potentially can be eliminated.

(39) According to USEPA (1999b, October), 75 percent of the vehicle mass (of a typical vehicle) is recycled when scrapped, and the remainder is landfilled. For simplicity, recycling is not included in the life-cycle model, and only landfilled waste is considered based upon the assumed vehicle weights:

| | |
|---|---|
| LD gasoline-powered "minivan": | 3,800 lbs. |
| LD CNG-powered "minivan": | 4,400 lbs. |
| MD gasoline-powered "shuttle bus": | 8,000 lbs. |
| MD diesel-powered "shuttle bus": | 12,000 lbs. |

## OPERATING (ECONOMIC) COSTS

(40) Vehicle economic operating costs are allocated on a "per mile" basis (only). There are several reasons for this: convention, as both much prior theoretical work as well as many practical applications (e.g., , Chira-Chavala, 1999; Dessouky and Adam, 1998a, b) utilize objective functions based on minimization of distance or distance-related cost; in practice, paratransit providers may utilize out-sourced vehicles, contracted on a "per mile" basis (Weidner, 2000); and, in practice, paratransit operators may be provided vehicles and compensated based upon minimization of distance (Weidner, 2000).

Relevant economic costs are:

- vehicle depreciation, based on allocation of vehicle purchase price (retail cost in 2000$)including ADA modification over the vehicle's useful life;
- fuel cost (retail cost in 2000$) calculated based upon fuel economy.

For the modeled vehicles, these costs (in 2000$) are calculated to be:

| | Retail price,$ | Deprec., $/mile | Fuel, $/gal | Fuel, MPG |
|---|---|---|---|---|
| LD-gas "minivan": | 20,900 | 0.232 | 1.55 | 20.1 |
| LD-CNG "minivan": | 25,850 | 0.287 | 0.35 | 5 |
| MD-gas "shuttle bus": | 40,700 | 0.233 | 1.55 | 11.2 |
| MD-diesel "shuttle bus": | 52,800 | 0.264 | 1.44 | 22.5 |

| | Maint., $/mile | Total Operating Cost, $/mi |
|---|---|---|
| LD-gas "minivan": | 0.074 | 0.375 |
| LD-CNG "minivan": | 0.092 | 0.449 |
| MD-gas "shuttle bus": | 0.074 | 0.445 |
| MD-diesel "shuttle bus": | 0.085 | 0.413 |

Driver and other overhead costs are not included among relevant costs because 1) they do not differ among vehicles or vehicle types, and 2) they are not relevant in terms of the contractual performance incentives and penalties by which paratransit operators are compensated (Access Services, Inc., 2000).

**Additional References Cited**

Access Services, Inc. (2000). (Access Contractor) "Term and Conditions," received from Los Angeles Metropolitan Transportation Authority.

Carslaw, D., & Fricker, N. (1995). Natural gas vehicles. *Chemistry and Industry*, 15, 593-596.

McCormick, R., Graboski, M., Alleman, T., & Yanowitz, J. (2000). Idle emissions from heavy-duty diesel and natural gas vehicles at high altitude. *Journal of the Air and Waste Management Association*, 50, 1992-1998.

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## APPENDIX B: VEHICLE (PARTIAL UNIT) UTILITY FACTOR BASIS

### Reference Values for Calculation of Unit Utility Factors

In general, because of assumed linear single-attribute value (utility) functions, single-attribute utility functions for damage indicators (attributes) $D_j$ may be expressed as:

$$u(D_j) = - \sum_i I_i D_{ij} / D_{j(REF)}, \tag{B1}$$

where

$$D_{ij} = \sum_k D_{ijk} \tag{B2}$$

in the case of impact-specific damage indicators ($D_{ijk}$, e.g., EPS and Eco-Indicator), and where

$$D_{j(REF)} \geq \max. \sum_i I_{i(REF)} D_{ij}. \tag{B3}$$

That is, the reference quantity $I_{i(REF)}$ is defined as the maximum feasible quantity of stressor i among the stressors and alternatives considered. (We assume that the linearity of the single-attribute preference function is valid over all outcome ranges; however, we wish to constrain the range considered to one that is realistic.)

The previous reference quantities are calculated based on the unit (per mile, per engine start, and per minute idle) vehicle emissions factors and an assumed "worst case" scenario based on the system simulated—the number of vehicles in daily use and foreseeable maximum distance, idling time, and engine starts per vehicle. (The unit emissions factors are reported in the main body and the latter values may be determined by system experimentation.) Alternatively, the reference values themselves may be directly determined based on experimentation, as a listing of system-wide stressor quantities (totals) is provided as a simulation output.

For illustration, we consider the four illustrative fleet compositions and operational results shown on Table B1. Total stressor quantities resultant of each scenario are calculated by multiplying unit stressor emissions factors (e.g., grams of stressor i per mile, data reported in main text body) and the respective scenario units (e.g., total number of miles, engine starts, etc.) for each vehicle type. And, the emissions are then summed across activities (e.g., transit, engine starts, etc.). These results shown on Table B2.

The reference quantities that we would utilize for this example are also shown on Table B2. The quantities are arbitrarily specified taking into account the fact that the scenarios do not necessarily represent the "worst possible case" for the particular fleet compositions for which actual emissions have been determined based on a particular demand. (Our "rule of thumb" is to specify the reference values as about twice the values expected from a "typical" scenario. The simulation program itself contains errors traps to ensure that calculated utility values for simulated system scenarios are within the expected range.)

Similarly, on the same example basis, we can calculate reference values for the damage indicators of interest, i.e., $D_{j(REF)}$, utilizing the reference quantities of Table B2 and the unit damage indicator values (data reported in main text body) and combining like indicators across impact categories (Equation B2) and stressors (Equation B1). The results are provided in Table B3. Reference values for Resource Depletion and Other Impacts impacts are simply the reference quantities ($I_{i(REF)}$) shown on Table B2; that is, for these, $D_{j(REF)} \equiv I_{i(REF)}$, where $I_i \in D_j$ in this case.

| Table B1. Basic Data for Illustrative Fleet Composition Example | | | | | |
|---|---|---|---|---|---|
| | | Alternative | | | |
| Vehicle (Type) | Variable | A | B | C | D |
| Type I (Gasoline-powered, light-duty "minivan") | Number of vehicles | 120 | 100 | 100 | 80 |
| | Vehicle miles | 94,800 | 83,500 | 73,550 | 58,800 |
| | Vehicle engine starts | 1,320 | 1,080 | 1,160 | 960 |
| | Vehicle minutes idling | 19,200 | 15,050 | 15,650 | 13,600 |
| Type II (CNG-powered, light-duty "minivan") | Number of vehicles | 80 | 140 | 120 | 100 |
| | Vehicle miles | 60,400 | 121,100 | 85,800 | 74,250 |
| | Vehicle engine starts | 840 | 1,330 | 1,360 | 1,210 |
| | Vehicle minutes idling | 12,400 | 19,700 | 19,200 | 16,950 |
| Type III (Gasoline-powered, medium-duty "shuttle bus") | Number of vehicles | 40 | 40 | 60 | 60 |
| | Vehicle miles | 30,050 | 28,400 | 45,900 | 46,500 |
| | Vehicle engine starts | 440 | 480 | 630 | 590 |
| | Vehicle minutes idling | 5,800 | 7,400 | 11,050 | 10,800 |
| Type IV (Diesel-powered, medium-duty "shuttle bus") | Number of vehicles | 40 | 0 | 0 | 40 |
| | Vehicle miles | 28,700 | 0 | 0 | 29,650 |
| | Vehicle engine starts | 410 | 0 | 0 | 450 |
| | Vehicle minutes idling | 6,050 | 0 | 0 | 6,850 |
| TOTAL, All Vehicle Types | Number of vehicles | 280 | 280 | 280 | 280 |
| | Vehicle miles | 213,950 | 233,300 | 205,250 | 209,200 |
| | Vehicle engine starts | 3,010 | 2,890 | 3,150 | 3,210 |
| | Vehicle minutes idling | 43,450 | 42,150 | 45,900 | 48,200 |

| Table B2. Life-Cycle Inventory for Alternatives in Illustrative Calculation (all quantities in kg unless otherwise noted) | | | | | |
|---|---|---|---|---|---|
| | Alternative | | | | Ref. Quan. |
| Stressor | A | B | C | D | $I_{i(REF)}$ |
| $CO_2$ ($CO_2$ equivalents) | 208,191 | 227,940 | 210,151 | 212,875 | 450,000 |
| CO | 896.56 | 941.76 | 973.91 | 954.46 | 2,000 |
| $NO_x$ ($NO_2$) | 414.68 | 369.54 | 337.75 | 441.02 | 900 |
| PM-10 | 32.50 | 36.19 | 32.88 | 32.55 | 75 |
| NMOG (VOC) | 134.02 | 132.39 | 121.60 | 138.34 | 250 |
| $SO_x$ ($SO_2$) | 228.46 | 239.07 | 217.08 | 223.45 | 400 |
| 1,3-Butadiene | 0.18 | 0.11 | 0.14 | 0.20 | 1 |
| Formaldehyde | 4.14 | 3.88 | 3.87 | 5.22 | 10 |
| Toluene | 2.51 | 2.22 | 2.83 | 2.79 | 5 |
| Benzene | 0.90 | 0.78 | 0.99 | 1.00 | 2 |
| Acetaldehyde | 0.56 | 0.36 | 0.31 | 0.61 | 2 |
| Methane | 403.45 | 802.38 | 572.12 | 496.05 | 1,600 |
| Methyl t-Butyl Ether (MTBE) | 1.34 | 1.24 | 1.55 | 1.45 | 3 |
| DPM-10 (diesel PM-10) | 1.87 | 0 | 0 | 1.95 | 5 |
| TRI emissions | 8.96 | 9.92 | 8.62 | 8.73 | 20 |
| Non-renewable energy use (units in Mjoules) | 1,766,630 | 1,879,210 | 1,793,773 | 1,821,412 | 4,000,000 |
| Fuel use (in gasoline-equivalents) (units in gallons) | 11,743 | 12,568 | 12,117 | 12,136 | 25,000 |
| Base-metal ore depletion | 14,341 | 15,923 | 13,800 | 13,982 | 32,000 |
| Precious-metal ore depletion | 2,733 | 3,036 | 2,629 | 2,664 | 6,000 |
| RCRA waste | 318.16 | 350.37 | 308.01 | 312.24 | 700 |
| Non-recycled solid waste | 1,142 | 1,221 | 1,068 | 1,139 | 2,500 |
| OPERATING COST ($) | 87,895 | 98,324 | 86,531 | 88,326 | |

**Table B3. Reference Values of $D_{j(REF)}$**

| Human Health End-Point | | Ecological End-Point | | | | Human Health Damage Potential | |
|---|---|---|---|---|---|---|---|
| EPS-CDALY[1,2] | Eco-Ind. DALY | EPS-NEX[1] | Eco-Ind. PDF | EPS-Base Cat. Cap. | EPS-Prod. Cap.[1,2] | USES-HTP | EPA-HHHRF |
| 4.3602 | 0.2371 | 6.2202E-9 | 5558 | 1605 | -1.9172E+4 | 2.86E+6 | 27,687 |

| Ecological Damage Potential | | | | | Human and Ecological Damage Potential | |
|---|---|---|---|---|---|---|
| USES-ETP[2] | EPA-THRF | EPA-AHRF | Acidification Pot. | Eutrophication Pot. | POCP | GWP |
| 3.15E+4 | 263 | 9,023 | 1,030 | 900 | 765 | 498,203 |

(1) For certain damage indicators, the EPS methodology considers both damages and beneficial consequences, for example, increased crop productive capacity due to carbon fertilization or reduction of global warming due to particulate emissions. And, the methodology considers these are "credits," which is why certain stressor damage values are indicated as a negative (-) quantity.

(2) EPS-CDALY, EPS-Productive Capacity (loss), and USES-ETP are constructed attributes, evaluated as noted in the main body.

**Calculation of "Partial Unit Utility Factors"**

Suppose instead of the above reference basis, we were interested in optimizing the itinerary of a single vehicle. And, suppose we believed the "worst case" itinerary for a single vehicle consisted of 200 miles of transit, 100 minutes of engine idling, and 10 engine starts. We calculate impacts for this case and use these as the basis for calculating "unit partial utility factors" and to illustrate the rescaling of these factors for any system or reference basis. First, we describe what we mean by a unit partial utility factor.

From Equation B1, it should be seen that the utility value of a particular damage indicator value (as an attribute) is a linear function of $I_i$, the stressor quantity, and, similarly, from Equation B2 that unit damage indicator values are the sum of impact-specific unit values. Moreover, from our equations (in the main text body) for the overall utility model, all of the component utility functions—$u_R(R)$, $u_O(O)$, $u_{HD}(HD)$, $u_{HP}(HP)$, $u_{ED}(ED)$, $u_{EP}(EP)$—are, likewise, linear combinations of component (damage indicator or constructed attribute) values, as these utility functions have been defined in the main body.

The point is that because of our particular preference assumptions and the linearity of the LCIA methods utilized, we can determine values of each of the above six functions on a unit basis—i.e., per mile of transit, per engine start, and per minute idling—for each vehicle type. And, the utility value of any itinerary, or sets of itineraries, can be calculated based on these unit factors. For example, if $u_R(R) = -x$ for one mile of transit for vehicle type A, then the utility value for two miles of transit is $-2x$—because of the way the factors have been normalized, i.e., based on a reference quantity. That is, the factors are *unit* utility factors; and, because each only represents a single utility component, we refer to them as being *partial unit* utility factors. Although this requires the determination of values for 72 factors, these must be determined only once; and, the resultant computational savings through their use is significant.

It should be seen that these factors, and calculated utility values, are relative to the reference basis. We first calculate unit partial utility factors for the four vehicle types on the above basis. Then, we illustrate how these factors can be rescaled for any system without recalculation of the individual values. As we explain later, we only wish to assess decision-maker preferences once; and, we assume that decision-maker preferences (scaling constants) have already been assessed for utility functions and consequences based upon the stressor quantities of Table B2, since preferences are relative to the range of outcomes considered. More specifically, as we describe later, by rescaling all utility functions (and reference quantities) by a constant factor, we can avoid the need to reassess decision-maker preferences.

We first determine stressor quantities representing the "worst case" for any vehicle type on the above basis. Then, we simply divide the previous reference quantities by a single factor representing the greatest ratio (where a ratio is calculated for each stressor). The results are provided in Table B4, where the greatest stressor ratio is seen to be 0.006. And, the new reference quantities shown in the last column on the Table are the original reference quantities (Table B3) multiplied by 0.006.

Next, we calculate $D_{j(REF)}$ for all damage indicators based on the new reference quantities, where $D_{j(REF)} = \sum_i I_{i(REF)} D_{ij} = \sum_k \sum_i I_{i(REF)} D_{ijk}$, whichever the case may be, and where values of $D_{ij}$ or $D_{ijk}$ are the unit damage indicator values reported in the main body. The results are provided in Table B5. Then, using the unit emissions factors and unit damage indicator values (both reported in main body), together with the above reference values, we calculate unit values of $I_i D_{ijk} / D_{j(REF)}$ for each vehicle type and activity. Calculated values for one vehicle type (gasoline-powered "minivan") are reported in Tables B6 through B8 for illustration.. These values represent the partial unit utility value due to a particular stressor, i.e., $u(I_i D_{ijk}) = - I_i D_{ijk} / D_{j(REF)}$. We then use these values to calculate the unit partial utility values of interest. That is, because of the commutative and associative properties of algebra, Equations B1 and B2 can be restated as $u(D_j) = - \sum_i I_i D_{ij} / D_{j(REF)} = - \sum_k \sum_i I_i D_{ijk} / D_{j(REF)} = \sum_k \sum_i u(I_i D_{ijk}) = - \sum_k \sum_i I_i D_{ijk} / D_{j(REF)}$.

| Table B4. Calculation of Scaling Factor For Reference Quantities and Attribute Scales (all quantities in kg unless otherwise noted) | | | | |
|---|---|---|---|---|
| Stressor | Itinerary Reference (Maximum) Quantity | Ref. Quan., $I_{i(REF)}$ | Ratio | New Ref. Quan, $I_{i(REF)}$ |
| $CO_2$ ($CO_2$ equivalents) | 589.42 | 450,000 | 0.0013 | 2700 |
| CO | 5.7970 | 2,000 | 0.0029 | 12 |
| $NO_x$ ($NO_2$) | 1.9579 | 900 | 0.0022 | 5.4 |
| PM-10 | 0.0811 | 75 | 0.0011 | 0.45 |
| NMOG (VOC) | 0.5327 | 250 | 0.0021 | 1.5 |
| $SO_x$ ($SO_2$) | 0.5117 | 400 | 0.0013 | 2.4 |
| 1,3-Butadiene | 0.0016 | 1 | 0.0016 | 0.006 |
| Formaldehyde | 0.0560 | 10 | 0.0056 | 0.06 |
| Toluene | 0.0255 | 5 | 0.0051 | 0.03 |
| Benzene | 0.0089 | 2 | 0.0045 | 0.012 |
| Acetaldehyde | 0.0050 | 2 | 0.0025 | 0.012 |
| Methane | 2.7083 | 1,600 | 0.0017 | 9.6 |
| Methyl t-Butyl Ether (MTBE) | 0.0135 | 3 | 0.0045 | 0.018 |
| DPM-10 (diesel PM-10) | 0.0300 | 5 | 0.0060 | 0.03 |
| TRI emissions | 0.0176 | 20 | 0.0009 | 0.12 |
| Non-renewable energy use including fuel consumption (units in Mjoules) | 10,225 | 6,750,000 | 0.0015 | 40,500 |
| Base-metal ore depletion | 28.75 | 32,000 | 0.0009 | 192 |
| Precious-metal ore depletion | 5.4805 | 6,000 | 0.0009 | 36 |
| RCRA waste | 0.6331 | 700 | 0.0009 | 4.2 |
| Non-recycled solid waste | 2.7280 | 2,500 | 0.0011 | 15 |

| Table B5. Damage Indicator Reference Values ($D_{j(REF)}$) for Calculation of "Unit Partial Utility Values" | | |
|---|---|---|
| Indicator Type | Indicator | $D_{j(REF)}$ |
| Human Health Damage (End-Point) | EPS CDALYs | 2.615E-02 |
| | Eco-Indicator DALYs | 1.422E-03 |
| Ecological Damage (End-Point) | EPS – NEX | 3.732E-11 |
| | Eco-Indicator PDF | 3.335E+01 |
| | EPS Base Cation Capacity | 9.630E+00 |
| | EPS Productive Capacity Loss | -1.149E+02 |
| Mid-Point (Hazard) | USES Human Toxicity Potential (USES-HTP) | 1.71E+04 |
| | EPA Human Health Hazard Ranking Factor (EPA-HHHRF) | 1.661E+02 |
| | USES Eco-Toxicity Potential (USES-ETP) | 1.89E+02 |
| | EPA Terrestrial Hazard Ranking Factor (EPA-THRF) | 1.578E+00 |
| | EPA Aquatic Hazard Ranking Factor (EPA-AHRF) | 5.414E+01 |
| | Acidification Potential | 6.189E+00 |
| | Eutrophication Potential | 5.400E+00 |
| | Photochemical Oxidant Creation Potential (POCP) | 4.593E+00 |
| | Global Warming Potential (GWP) | 2.989E+03 |
| Resource Depletion | Base Metal Consumption | 192 |
| | Precious Metal Consumption | 36 |
| | Nonrenewable Energy Consumption | 40,500 |
| Other Impacts | TRI Emissions | 0.12 |
| | RCRA Waste Generation | 4.2 |
| | Solid (non-RCRA) Waste Generation | 15 |

| Table B6. Values of $I_iD_{ijk} / D_{j(REF)}$ for Vehicle Type 1 (Light-Duty, Gasoline-Powered "Minivan") Per Mile | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Stressor** | **Impact Category, LCIA Indicator, and Value of $I_iD_{ijk} / D_{j(REF)}$** | | | | | | | |
| | | | Human Toxicity | | | | | |
| | Global Warming | | Toxic Effects | | Oxidant Effects | | Species Loss | |
| | EPS-CDALY | Eco-In DALY | EPS-CDALY | Eco-In DALY | EPS-CDALY | Eco-In DALY | EPS-NEX | Eco-In PDF |
| $CO_2$ | 4.311E-05 | 1.281E-04 | | | | | 2.928E-04 | |
| CO | 4.523E-07 | | 1.666E-09 | 1.555E-06 | | | 3.064E-06 | |
| $NO_x$ | -1.806E-07 | | 5.950E-06 | 6.817E-05 | 3.445E-09 | | 2.186E-06 | 1.864E-04 |
| PM-10 | -2.456E-08 | | 3.068E-06 | 3.903E-05 | | | -4.283E-07 | |
| (NM)VOC | 1.938E-07 | | | | 1.297E-07 | 2.019E-07 | 1.656E-06 | |
| $SO_x$ | -5.094E-07 | | 1.541E-05 | 4.158E-05 | | | -8.537E-06 | 3.381E-05 |
| 1,3-Butadiene | 1.641E-10 | | 9.935E-10 | 3.333E-09 | 1.434E-10 | 3.945E-10 | 1.117E-09 | |
| Formaldehyde | 7.109E-10 | | 2.655E-09 | 9.060E-10 | 3.530E-11 | 1.015E-09 | 4.842E-09 | |
| Toluene | 2.616E-09 | | | | 1.276E-09 | 5.738E-09 | 2.235E-08 | 4.318E-11 |
| Benzene | 1.148E-09 | | 1.694E-09 | 3.692E-09 | 3.164E-10 | 6.911E-10 | 7.822E-09 | 1.732E-10 |
| Acetaldehyde | 1.308E-10 | | | 4.557E-11 | 7.606E-11 | 2.869E-10 | 1.117E-09 | |
| Methane | 1.061E-08 | 2.692E-08 | | | 2.904E-11 | 7.831E-11 | 7.203E-08 | |
| MTBE | 1.831E-09 | | | | 5.782E-10 | 9.806E-10 | 1.564E-08 | |
| DPM-10 | | | | | | | | |
| | | | | | | | | |
| | EPS Prod. Cap. | Base Cat.Cap. | USES-HTP | EPA-HHHRF | USES-ETP | EPA-THRF | EPA-AHRF | Acid. Pot. |
| | 3.089E-04 | 2.986E-04 | 3.70E-07 | 2.407E-04 | 2.36E-08 | 1.554E-04 | 2.716E-04 | 2.985E-04 |
| | | | | | | | | |
| | Eutroph. Pot. | POCP | GWP | | | | | |
| | 2.015E-04 | 2.591E-04 | 2.949E-04 | | | | | |
| | | | | | | | | |
| | Energy + Fuel Cons. | | Base Metal | Prec. Metal | TRI Emis. | RCRA Waste | Solid Waste | |
| | 3.201E-04 | | 3.473E-04 | 3.534E-04 | 3.500E-04 | 3.490E-04 | 3.200E-04 | |

**Table B7. Values of $I_iD_{ijk} / D_{j(REF)}$ for Vehicle Type 1 (Light-Duty, Gasoline-Powered "Minivan") Per Minute Idling**

| **Stressor** | **Impact Category, LCIA Indicator, and Value of $I_iD_{ijk} / D_{j(REF)}$** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Human Toxicity | | | | | |
| | Global Warming | | Toxic Effects | | Oxidant Effects | | Species Loss | |
| | EPS-CDALY | Eco-In DALY | EPS-CDALY | Eco-In DALY | EPS-CDALY | Eco-In DALY | EPS-NEX | Eco-In PDF |
| $CO_2$ | 7.656E-06 | 2.274E-05 | | | | | 5.199E-05 | |
| CO | 9.342E-07 | | 3.441E-09 | 3.212E-06 | | | 6.328E-06 | |
| $NO_x$ | -3.137E-08 | | 1.034E-06 | 1.184E-05 | 5.984E-10 | | 3.798E-07 | 3.238E-05 |
| PM-10 | -1.494E-09 | | 1.865E-07 | 2.373E-06 | | | -2.605E-08 | |
| (NM)VOC | 1.326E-07 | | | | 8.873E-08 | 1.381E-07 | 1.133E-06 | |
| $SO_x$ | -3.198E-08 | | 9.673E-07 | 2.611E-06 | | | -5.361E-07 | 2.123E-06 |
| 1,3-Butadiene | 9.843E-10 | | 5.961E-09 | 2.000E-08 | 8.604E-10 | 2.367E-09 | 6.704E-09 | |
| Formaldehyde | 4.812E-09 | | 1.797E-08 | 6.133E-09 | 2.389E-10 | 6.869E-09 | 3.278E-08 | |
| Toluene | 1.535E-08 | | | | 7.484E-09 | 3.367E-08 | 1.311E-07 | 2.533E-10 |
| Benzene | 6.726E-09 | | 9.925E-09 | 2.162E-08 | 1.853E-09 | 4.048E-09 | 4.581E-08 | 1.014E-09 |
| Acetaldehyde | 7.847E-10 | | | 2.734E-10 | 4.564E-10 | 1.722E-09 | 6.704E-09 | |
| Methane | 6.417E-08 | 1.628E-07 | | | 1.756E-10 | 4.735E-10 | 4.355E-07 | |
| MTBE | 7.673E-09 | | | | 2.423E-09 | 4.109E-09 | 6.555E-08 | |
| DPM-10 | | | | | | | | |
| | | | | | | | | |
| | EPS Prod. Cap. | Base Cat.Cap. | USES-HTP | EPA-HHHRF | USES-ETP | EPA-THRF | EPA-AHRF | Acid. Pot. |
| | 5.008E-05 | 3.241E-05 | 1.61E-06 | 2.387E-04 | 1.54E-07 | 1.858E-04 | 2.111E-04 | 3.241E-05 |
| | | | | | | | | |
| | Eutroph. Pot. | POCP | GWP | | | | | |
| | 3.500E-05 | 4.193E-04 | 5.963E-05 | | | | | |
| | | | | | | | | |
| | Energy + Fuel Cons. | | Base Metal | Prec. Metal | TRI Emis. | RCRA Waste | Solid Waste | |
| | 5.820E-05 | | 2.708E-06 | 2.111E-06 | | 1.214E-05 | | |

| Table B8. Values of $I_iD_{ijk} / D_{j(REF)}$ for Vehicle Type 1 (Light-Duty, Gasoline-Powered "Minivan") Per Engine Start | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Stressor** | **Impact Category, LCIA Indicator, and Value of $I_iD_{ijk} / D_{j(REF)}$** | | | | | | | |
| | | | Human Toxicity | | | | | |
| | Global Warming | | Toxic Effects | | Oxidant Effects | | Species Loss | |
| | EPS-CDALY | Eco-In DALY | EPS-CDALY | Eco-In DALY | EPS-CDALY | Eco-In DALY | EPS-NEX | Eco-In PDF |
| $CO_2$ | 5.185E-06 | 1.540E-05 | | | | | 3.521E-05 | |
| CO | 4.424E-07 | | 1.629E-09 | 1.521E-06 | | | 2.997E-06 | |
| $NO_x$ | -6.771E-08 | | 2.231E-06 | 2.556E-05 | 1.292E-09 | | 8.199E-07 | 6.989E-05 |
| PM-10 | -9.958E-10 | | 1.244E-07 | 1.582E-06 | | | -1.736E-08 | |
| (NM)VOC | 1.054E-07 | | | | 7.052E-08 | 1.098E-07 | 9.002E-07 | |
| $SO_x$ | -2.164E-08 | | 6.544E-07 | 1.766E-06 | | | -3.626E-07 | 1.436E-06 |
| 1,3-Butadiene | 7.109E-10 | | 4.305E-09 | 1.444E-08 | 6.214E-10 | 1.710E-09 | 4.842E-09 | |
| Formaldehyde | 3.664E-09 | | 1.368E-08 | 4.669E-09 | 1.819E-10 | 5.230E-09 | 2.495E-08 | |
| Toluene | 1.203E-08 | | | | 5.868E-09 | 2.640E-08 | 1.028E-07 | 1.986E-10 |
| Benzene | 5.304E-09 | | 7.827E-09 | 1.705E-08 | 1.461E-09 | 3.192E-09 | 3.613E-08 | 7.999E-10 |
| Acetaldehyde | 5.667E-10 | | | 1.975E-10 | 3.296E-10 | 1.243E-09 | 4.842E-09 | |
| Methane | 1.952E-08 | 4.951E-08 | | | 5.341E-11 | 1.440E-10 | 1.325E-07 | |
| MTBE | 6.496E-09 | | | | 2.051E-09 | 3.479E-09 | 5.550E-08 | |
| DPM-10 | | | | | | | | |
| | | | | | | | | |
| | EPS Prod. Cap. | Base Cat.Cap. | USES-HTP | EPA-HHHRF | USES-ETP | EPA-THRF | EPA-AHRF | Acid. Pot. |
| | 3.746E-05 | 5.363E-05 | 1.28E-06 | 1.504E-04 | 1.18E-07 | 1.456E-04 | 1.673E-04 | 5.366E-05 |
| | | | | | | | | |
| | Eutroph. Pot. | POCP | GWP | | | | | |
| | 7.556E-05 | 2.167E-04 | 3.911E-05 | | | | | |
| | | | | | | | | |
| | Energy + Fuel Cons. | | Base Metal | Prec. Metal | TRI Emis. | RCRA Waste | Solid Waste | |
| | 3.985E-05 | | 1.844E-06 | 1.444E-06 | | 8.333E-06 | | |

CALCULATION OF HUMAN HEALTH POTENTIAL DAMAGE (HD) AND ECOLOGICAL POTENTIAL DAMAGE (ED) PARTIAL UNIT UTILITY FACTORS

Our basic decision model, presented in the main body, combines LCIA damage indicators (as decision attributes) from multiple LCIA mid-point and end-point methods, as well as attributes for resource depletion and "other impacts." The overall objectives hierarchy including attributes for human health and ecological damage may be seen in Figure 1. It should be seen that attribute and utility values are first calculated for human health potential damages (HD), ecological potential damages (ED), human health damage potential (HP), and ecological damage potential (EP) and then, ultimately, combined in a single utility value.

For the objectives (and attributes) pertaining to human health and ecological potential damages, i.e., based on end-point potential damage indicators,

$$\boldsymbol{u}_{Xli}(a_{xli}) = -\sum_j \{I_i \sum_k [(D_{ijk})(\boldsymbol{b}_{Xlijk})] / D_{j(REF)}\}, \qquad \forall\, D_j \in A_{Xl},\ X \in \{HD, ED\}, \qquad \text{(B4)}$$

$$\boldsymbol{u}_{Xl}(a_{Xl}) = \sum_i \boldsymbol{u}_{Xli}(a_{Xli}), \qquad \text{(B5)}$$

where $A_{Xl}$ is a decision attribute for Human Health Potential Damages (HD) or Ecological Potential Damage (ED), $a_{Xli}$ is the value of $A_{Xl}$ for stressor i, and $a_{Xl}$ is the value of $A_{Xl}$ over all stressors. It should be seen that the first equation can be rearranged as:

$$\boldsymbol{u}_{Xli}(a_{xli}) = -(\boldsymbol{b}_{Xlijk})\{\sum_j \sum_k [(I_i D_{ijk}) / D_{j(REF)}]\}, \qquad \text{(B6)}$$

where the quantity $[(I_i D_{ijk}) / D_{j(REF)}]$ has already been calculated (Tables B6-B9). (Quantities shown in bold italic typeface are normal, triangular fuzzy numbers as explained in the main body.) It should be noted that the quantities $\boldsymbol{b}_{Xlijk}$ are normalized values such that the minimum value of $\boldsymbol{u}_{Xl}(a_{Xl})$ for any $a_{Xl}$ is "about –1," since the quantity is a fuzzy quantity, and the maximum value is the degenerate fuzzy number (0, 0, 0).

Utility values for the main sub-objectives, $\boldsymbol{u}_{HD}(HD)$ and $\boldsymbol{u}_{ED}(ED)$, are calculated as follows, because of our assumed preference conditions and resultant, additive decomposition form:

$$\boldsymbol{u}_{HD}(HD) = \sum_l w_{Xl}\, \boldsymbol{u}_{Xl}(a_{Xl}),\ X \in HD; \qquad \boldsymbol{u}_{ED}(ED) = \sum_l w_{Xl}\, \boldsymbol{u}_{Xl}(a_{Xl}),\ X \in ED. \qquad \text{(B7-8)}$$

In the case of health potential damage, $\boldsymbol{u}_{HD}(HD)$ is evaluated based on a single attribute that, in turn, is evaluated (through Equation B4) utilizing the LCIA damage indicators Eco-Indicator DALY and EPS-CDALY (a constructed attribute). For ecological potential damage, $\boldsymbol{u}_{ED}(ED)$ is evaluated based on three attributes: EPS Soil Cation Capacity, EPS Productive Capacity Loss (a constructed attribute), and an attribute for species loss that is evaluated utilizing Equation B4 and the LCIA damage indicator of EPS-NEX and Eco-Indicator PDF. Values of $\boldsymbol{b}_{Xlijk}$ and $w_{Xl}$, based on assumed decision-maker preferences, are provided in Appendix C.

The results, for the reference basis noted earlier (the quantities in Table B4), are provided in Tables B7 and B8.

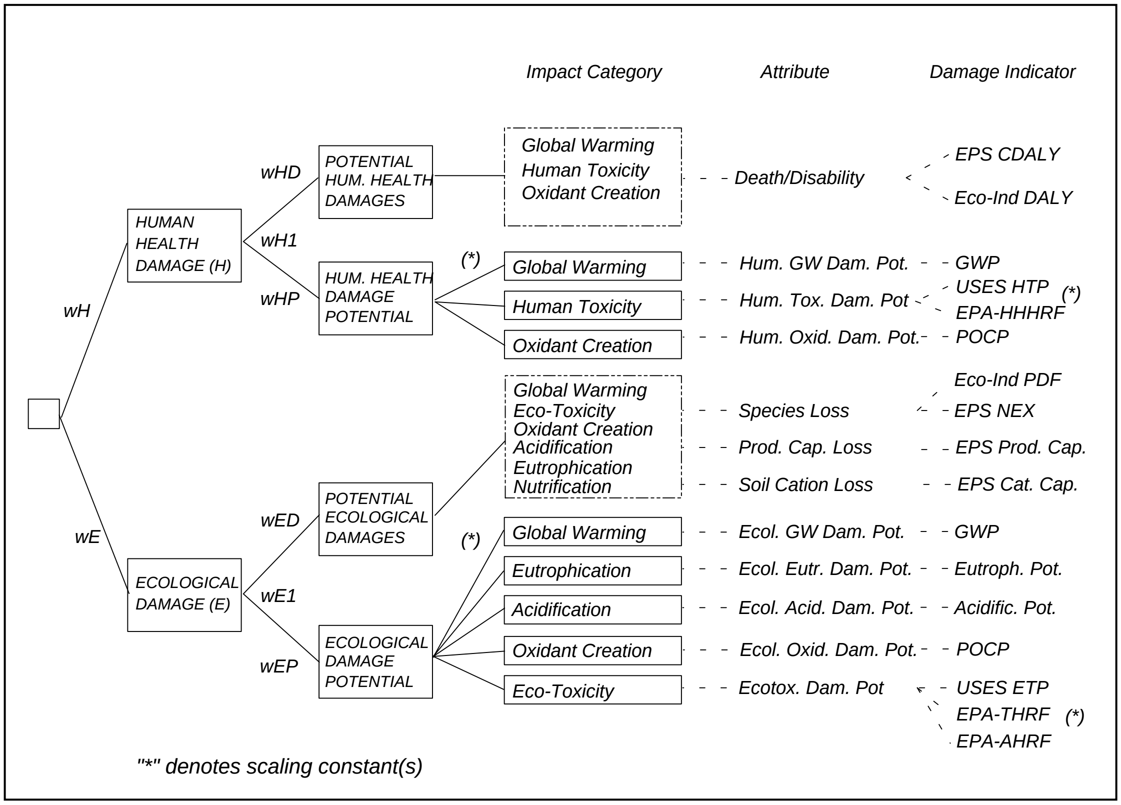


Figure B1. Combined Fundamental and Means-Ends Objectives Network Including Both Mid-Point (Damage Potential) and End-Point (Potential Damage) Objectives and Attributes

| Table B7. Calculated "Unit Partial Utility Values" for Human Health Damage Potential Attribute ($A_H$) | | |
|---|---|---|
| Veh. Type | Basis | $u_{HD}(HD) = u(a_{H1})$ |
| 1 | Mile | - (1.066E-4 1.588E-4, 2.320E-4) |
| | Minute Idle | - (1.762E-5, 2.557E-5, 3.692E-5) |
| | Engine Start | - (1.684E-5, 2.503E-5, 3.621E-5) |
| 2 | Mile | - (1.297E-4, 1.933E-4, 2.820E-4) |
| | Minute Idle | - (7.287E-6, 1.101E-5, 1.598E-5) |
| | Engine Start | - (4.938E-6, 7.460E-6, 1.083E-5) |
| 3 | Mile | - (1.615E-4, 2.407E-4, 3.511E-4) |
| | Minute Idle | - (3.159E-5, 4.573E-5, 6.595E-5) |
| | Engine Start | - (3.892E-5, 5.838E-5, 8.400E-5) |
| 4 | Mile | - (8.717E-4, 1.287E-3, 1.966E-3) |
| | Minute Idle | - (2.823E-4, 4.140E-4, 6.398E-4) |
| | Engine Start | - (1.964E-4, 2.875E-4, 4.418E-4) |

| Table B8. Calculated "Unit Partial Utility Values" for Ecological Damage Potential Attribute ($A_E$) | | | | | |
|---|---|---|---|---|---|
| Veh. Type | Basis | $u(a_{E1})$ (Species Loss) | $u(a_{E2})$ (Prod. Cap. Loss) | $u(a_{E3})$ (Soil Cation Cap.) | $u_{ED}(ED)$ |
| 1 | Mile | - (3.407E-4, 3.724E-4, 4.142E-4) | (3.089E-4, 3.089E-4, 3.089E-4) | - (2.986E-4, 2.986E-4, 2.986E-4) | - (1.533E-4, 1.720E-4, 1.967E-4) |
| | Minute Idle | - (6.722E-5, 7.240E-5, 7.930E-5) | (5.008E-5, 5.008E-5, 5.008E-5) | - (3.241E-5, 3.241E-5, 3.241E-5) | - (2.985E-5, 3.291E-5, 3.698E-5) |
| | Engine Start | - (5.455E-5, 6.537E-5, 7.984E-5) | (3.746E-5, 3.746E-5, 3.746E-5) | - (5.363E-5, 5.363E-5, 5.363E-5) | - (2.867E-5, 3.505E-5, 4.359E-5) |
| 2 | Mile | - (4.407E-4, 4.883E-4, 5.514E-4) | (3.443E-4, 3.443E-4, 3.443E-4) | - (3.443E-4, 3.443E-4, 3.443E-4) | - (2.084E-4, 2.365E-4, 2.737E-4) |
| | Minute Idle | - (1.929E-5, 2.310E-5, 2.819E-5) | (1.348E-5, 1.348E-5, 1.348E-5) | - (1.722E-5, 1.722E-5, 1.722E-5) | - (9.845E-6, 1.209E-5, 1.510E-5) |
| | Engine Start | - (1.325E-5, 1.585E-5, 1.933E-5) | (9.267E-6, 9.267E-6, 9.267E-6) | - (1.171E-5, 1.171E-5, 1.171E-5) | - (6.745E-6, 8.279E-6, 1.033E-5) |
| 3 | Mile | - (5.319E-4, 5.942E-4, 6.727E-4) | (4.742E-4, 4.742E-4, 4.742E-4) | - (4.412E-4, 4.412E-4, 4.412E-4) | - (2.384E-4, 2.752E-4, 3.215E-4) |
| | Minute Idle | - (1.204E-4, 1.292E-4, 1.410E-4) | (8.792E-5, 8.792E-5, 8.792E-5) | - (5.616E-5, 5.616E-5, 5.616E-5) | - (5.372E-5, 5.891E-5, 6.587E-5) |
| | Engine Start | - (1.042E-4, 1.406E-4, 1.893E-4) | (5.414E-5, 5.414E-5, 5.414E-5) | - (1.653E-4, 1.653E-4, 1.653E-4) | - (6.781E-5, 8.928E-5, 1.180E-4) |
| 4 | Mile | - (4.687E-4, 5.919E-4, 7.562E-4) | (3.546E-4, 3.546E-4, 3.546E-4) | - (6.943E-4, 6.943E-4, 6.943E-4) | - (2.675E-4, 3.402E-4, 4.371E-4) |
| | Minute Idle | - (3.932E-5, 4.893E-5, 6.174E-5) | (2.829E-5, 2.829E-5, 2.829E-5) | - (5.408E-5, 5.408E-5, 5.408E-5) | - (2.231E-5, 2.789E-5, 3.554E-5) |
| | Engine Start | - (4.273E-5, 4.926E-5, 5.797E-5) | (2.477E-5, 2.477E-5, 2.477E-5) | - (3.685E-5, 3.685E-5, 3.685E-5) | - (2.307E-5, 2.692E-5, 3.206E-5) |

Next, we calculate similar values for the mid-point-based objectives $u_{HP}(HP)$ and $u_{EP}(EP)$, Human Health Damage Potential and Ecological Damage Potential, respectively, including their component attributes.

From our decision model (presented in the main text body), there are two lowest-level attributes, Human Toxicity Damage Potential (HTDP) and Eco-Toxicity Damage Potential (ETDP); and, we evaluate these first. From the decision model:

$$\boldsymbol{g}_{Xl} = \sum_k \{[h_{lk}\, \boldsymbol{e}_{lk}\, (\sum_i I_i DP_{ilk}) / DP_{lk(REF)}] / [\sum_k h_{lk}\, \boldsymbol{e}_{lk}]\}, \qquad l = 1, 2, \ldots; X \in \{HTDP, ETDP\}. \quad (B9)$$

Here, the attribute HTDP is evaluated using the LCIA damage indicators ($DP_{ilk}$'s) USES Human Toxic Potential (USES-HTP) and EPA's Human Health Hazard Ranking Factor (EPA-HHHRF); and the attribute ETDP is evaluated based on the damage indicators USES Eco-Toxicity Potential (a constructed attribute, USES-ETP) and EPA's Terrestrial Hazard Ranking Factor (EPA-THRF) and Aquatic Hazard Ranking Factor (EPA-AHRF).

The quantity $\sum_i I_i DP_{ilk}) / DP_{lk(REF)}$ was evaluated previously (e.g., Tables B6-8); and, assumed values of the scaling constants $h_{lk}$ and $\boldsymbol{e}_{lk}$ are provided in Appendix C. The results, i.e., calculated values of HTDP and ETDP are provided in Table B9. Here, we defuzzify the values as a convenience for use in subsequent calculations and accept the (small) loss of information that results.

The remaining damage potential attributes, evaluated based upon a single LCIA unit damage indicator ($DP_{ijk}$), are simply evaluated as:

$$g_{Xl} = (\sum_i I_i DP_{ilk}) / DP_{lk(REF)}, \qquad l = 1, 2, \ldots; X \in \{HP, EP\} \qquad (B10)$$

where utility values for damage attributes are calculated as:

$$u(g_{Xl}) = - g_{Xl}. \qquad (B11)$$

Finally, values for the decision attributes $\boldsymbol{u}_X(X)$, $X \in \{HP, EP\}$, are evaluated as

$$\boldsymbol{u}_X(X) = \sum_l \{[c_{Xl}\, \boldsymbol{d}_{Xl}\, u(g_{Xl})] / [\sum_j c_{Xj}\, \boldsymbol{d}_{Xj}]\}. \qquad (B12)$$

As before, values of $I_i DP_{ilk}) / DP_{lk(REF)}$ have already been calculated (e.g., B6-B8); and, assumed values of $c_{Xl}\, \boldsymbol{d}_{Xl}$ are provided in Appendix C. Unit partial utility factors for human health damage potential and ecological damage potential $u_{HP}(HP)$ and $u_{EP}(EP)$ are provided in Table B-10.

## CALCULATION OF RESOURCE DEPLETION AND OTHER IMPACTS PARTIAL UNIT UTILITY FACTORS

As noted before, the reference basis (quantities) for Resource Depletion and Other Impacts attributes are simply the reference quantities shown in Table B4. Unit partial utility factors for the objectives are provided in Table B11.

| **Table 9. Calculated Values of Constructed Attributes Human Toxicity Damage Potential (HTDP) and Eco-Toxicity Damage Potential (ETDP)** | | | | | |
|---|---|---|---|---|---|
| Veh. Type | Basis | HTDP | Defuzzified Value | ETDP | Defuzzified Value |
| 1 | Mile | (1.234E-7, 3.701E-7, 2.415E-4) | 8.065E-5 | (1.032E-8, 2.356E-8, 6.026E-5) | 2.010E-5 |
| | Minute Idle | (5.382E-7, 1.615E-6, 2.419E-4) | 8.135E-5 | (6.767E-8, 1.544E-7, 5.628E-5) | 1.883E-5 |
| | Engine Start | (4.253E-7, 1.276E-6, 1.530E-4) | 5.155E-5 | (5.133E-8, 1.176E-7, 4.436E-5) | 1.484E-5 |
| 2 | Mile | (4.674E-8, 1.402E-7, 2.924E-4) | 9.753E-5 | (1.382E-7, 3.153E-7, 9.543E-5) | 3.193E-5 |
| | Minute Idle | (3.637E-9, 1.091E-8, 1.761E-5) | 5.874E-6 | (7.576E-8, 1.729E-7, 1.407E-5) | 4.772E-6 |
| | Engine Start | (2.485E-9, 7.454E-9, 1.202E-5) | 4.010E-6 | (5.204E-8, 1.187E-7, 9.619E-6) | 3.263E-6 |
| 3 | Mile | (4.256E-7, 1.277E-6, 4.402E-4) | 1.473E-4 | (4.649E-8, 1.061E-7, 9.468E-5) | 3.161E-5 |
| | Minute Idle | (8.951E-7, 2.685E-6, 5.178E-4) | 1.738E-4 | (1.110E-6, 2.533E-6, 2.564E-4) | 8.667E-5 |
| | Engine Start | (1.057E-6, 3.172E-6, 4.551E-4) | 1.531E-4 | (1.292E-7, 2.948E-7, 1.038E-4) | 3.473E-5 |
| 4 | Mile | (6.681E-4, 2.004E-3, 4.574E-3) | 2.415E-3 | (8.783E-4, 2.004E-3, 4.214E-3) | 2.366E-3 |
| | Minute Idle | (2.556E-4, 7.668E-4, 1.599E-3) | 8.739E-4 | (3.361E-4, 7.669E-4, 1.577E-3) | 8.932E-4 |
| | Engine Start | (1.734E-4, 5.201E-4, 1.542E-3) | 7.451E-4 | (2.279E-4, 5.202E-4, 1.069E-3) | 6.059E-4 |

| **Table 10. Calculated Values of Attributes Human Health Damage Potential ($G_{HP}$) and Ecological Damage Potential ($G_{EP}$) and Attribute "Unit Partial Utility Values"** | | | | | |
|---|---|---|---|---|---|
| Veh. Type | Basis | $\boldsymbol{g}_{HP}$ | $u_{HP}(HP) = u_{HP}(\boldsymbol{g}_{HP})$ per Basis Unit | $\boldsymbol{g}_{EP}$ | $u_{EP}(EP) = u_{EP}(\boldsymbol{g}_{EP})$ per Basis Unit |
| 1 | Mile | (6.091E-5, 1.748E-4, 5.905E-4) | - 2.754E-4 | (7.068E-5, 2.277E-4, 7.094E-4) | - 3.359E-4 |
| | Minute Idle | (2.503E-5, 7.181E-5, 3.501E-4) | - 1.490E-4 | (1.541E-5, 4.966E-5, 2.397E-4) | - 1.016E-4 |
| | Engine Start | (1.606E-5, 4.609E-5, 2.025E-4) | - 8.822E-5 | (1.030E-5, 3.318E-5, 1.732E-4) | - 7.223E-5 |
| 2 | Mile | (7.596E-5, 2.179E-4, 7.134E-4) | - 3.358E-4 | (8.956E-5, 2.886E-4, 8.918E-4) | - 4.233E-4 |
| | Minute Idle | (3.272E-6, 9.388E-6, 2.771E-5) | - 1.346E-5 | (3.615E-6, 1.165E-5, 4.168E-5) | - 1.898E-5 |
| | Engine Start | (2.245E-6, 6.441E-6, 1.900E-5) | - 9.230E-6 | (2.486E-6, 8.009E-6, 2.856E-5) | - 1.302E-5 |
| 3 | Mile | (9.684E-5, 2.779E-4, 9.557E-4) | - 4.435E-4 | (1.066E-4, 3.436E-4, 1.123E-3) | - 5.244E-4 |
| | Minute Idle | (5.039E-5, 1.446E-4, 6.942E-4) | - 2.964E-4 | (3.173E-5, 1.023E-4, 4.888E-4) | - 2.076E-4 |
| | Engine Start | (3.802E-5, 1.091E-4, 5.182E-4) | - 2.218E-4 | (1.503E-5, 4.842E-5, 4.249E-4) | - 1.628E-4 |
| 4 | Mile | (5.171E-4, 1.484E-3, 3.227E-3) | - 1.742E-3 | (2.484E-4, 8.003E-4, 2.806E-3) | - 1.285E-3 |
| | Minute Idle | (1.747E-4, 5.013E-4, 1.033E-3) | - 5.697E-4 | (7.378E-5, 2.377E-4, 7.482E-4) | - 3.532E-4 |
| | Engine Start | (1.507E-4, 4.325E-4, 1.292E-3) | - 6.251E-4 | (5.377E-5, 1.733E-4, 7.796E-4) | - 3.355E-4 |

| Table 11. Calculated "Unit Partial Utility Values" for Resource Depletion (R) and other Impacts (O) Attributes | | | |
|---|---|---|---|
| Veh. Type | Basis | $u_R(R)$ | $u_O(O)$ |
| 1 | Mile | -3.328E-04 | -3.452E-04 |
| | Minute Idle | -3.582E-05 | -3.642E-06 |
| | Engine Start | -2.453E-05 | -2.500E-06 |
| 2 | Mile | -3.286E-04 | -3.662E-04 |
| | Minute Idle | -2.713E-06 | -2.857E-07 |
| | Engine Start | -1.884E-06 | -1.429E-07 |
| 3 | Mile | -4.657E-04 | -3.309E-04 |
| | Minute Idle | -6.403E-05 | -1.115E-05 |
| | Engine Start | -2.867E-05 | -2.929E-06 |
| 4 | Mile | -3.052E-04 | -3.581E-04 |
| | Minute Idle | -4.211E-05 | -3.930E-06 |
| | Engine Start | -2.861E-05 | -2.643E-06 |

USE OF UNIT PARTIAL UTILITY VALUES

As presented in the main body, the final decision model is given as:

$$u(\text{alt.}) = w_H\, u(H) + w_E\, u(E) + w_R\, u(R) + w_O\, u(O), \text{ where} \quad \text{(B13)}$$

$$\boldsymbol{u}_H(H) = w_{HD}\boldsymbol{u}_{HD}(HD) + w_{HP}\boldsymbol{u}_{HP}(HP) + w_{H1}\boldsymbol{u}_{HD}(HD)\boldsymbol{u}_{HP}(HP), \quad \text{(B14)}$$

$$\boldsymbol{u}_E(E) = w_{ED}\boldsymbol{u}_{ED}(ED) + w_{EP}\boldsymbol{u}_{BEP}(EP) + w_{E1}\boldsymbol{u}_{ED}(ED)\boldsymbol{u}_{EP}(EP), \quad \text{(B15)}$$

$$u_R(R) = \textstyle\sum_j w_{Rj}\, [-(I_j / I_{j(REF)})],\ I_j \in \{R\}, \quad \text{(B16)}$$

$$u_O(O) = \textstyle\sum_j w_{Oj}\, [-(I_j / I_{j(REF)})],\ I_j \in \{O\}, \quad \text{(B17)}$$

$$w_{H1} = 1 - w_{HD} - w_{HP}, \quad \text{(B18)}$$

$$w_{E1} = 1 - w_{ED} - w_{EP}, \quad \text{(B19)}$$

$$w_H + w_E + w_R + w_O = 1, \quad \text{(B20)}$$

where illustrative (assumed) values of all remaining scaling constants are provided in Appendix C.

Thus, for a given itinerary or sets of itineraries, where the total numbers of miles, engines starts, and engine idling minutes are known by vehicle type (k),

$$u_{HD}(HD) = \textstyle\sum_{k=1}^{K} (\Lambda_k)[v_{HD}(HD)_{D,\,k}] + \sum_{k=1}^{K} (\Delta_k)[v_{HD}(HD)_{I,\,k}] + \sum_{k=1}^{K} (\Omega_k)[v_{HD}(HD)_{S,\,k}] \quad \text{(B21)}$$

$$u_{HP}(HP) = \textstyle\sum_{k=1}^{K} (\Lambda_k)[v_{HP}(HP)_{D,\,k}] + \sum_{k=1}^{K} (\Delta_k)[v_{HP}(HP)_{I,\,k}] + \sum_{k=1}^{K} (\Omega_k)[v_{HP}(HP)_{S,\,k}] \quad \text{(B22)}$$

$$u_{ED}(ED) = \textstyle\sum_{k=1}^{K} (\Lambda_k)[v_{ED}(ED)_{D,\,k}] + \sum_{k=1}^{K} (\Delta_k)[v_{ED}(ED)_{I,\,k}] + \sum_{k=1}^{K} (\Omega_k)[v_{ED}(ED)_{S,\,k}] \quad \text{(B23)}$$

$$u_{EP}(EP) = \textstyle\sum_{k=1}^{K} (\Lambda_k)[v_{EP}(EP)_{D,\,k}] + \sum_{k=1}^{K} (\Delta_k)[v_{EP}(EP)_{I,\,k}] + \sum_{k=1}^{K} (\Omega_k)[v_{EP}(EP)_{S,\,k}] \quad \text{(B24)}$$

$$u_R(R) = \textstyle\sum_{k=1}^{K} (\Lambda_k)[v_R(R)_{D,\,k}] + \sum_{k=1}^{K} (\Delta_k)[v_R(R)_{I,\,k}] + \sum_{k=1}^{K} (\Omega_k)[v_R(R)_{S,\,k}] \quad \text{(B25)}$$

$$u_O(O) = \textstyle\sum_{k=1}^{K} (\Lambda_k)[v_O(O)_{D,\,k}] + \sum_{k=1}^{K} (\Delta_k)[v_O(O)_{I,\,k}] + \sum_{k=1}^{K} (\Omega_k)[v_O(O)_{S,\,k}], \quad \text{(B26)}$$

where $\Lambda_k$, $\Delta_k$, and $\Omega_k$ denote the distance (miles), engine idling (minutes), and engine starts (number), respectively, of vehicle type k; and, the terms $v_X(X)_{Y,k}$, where $X \in$ {HD, HP, ED, EP, R, O} and $Y \in$ {Distance [D], Idling [I], Starts [S]} are the respective unit partial utility factors (for vehicle type k) described and calculated previously.

## RESCALING OF UNIT PARTIAL UTILITY FACTORS

Finally, it is assumed that decision-maker preferences, i.e., the preference-based scaling constants presented in Appendix C, have been assessed for a particular set of outcomes (attribute values)—specifically, consequences (damage or attribute values) corresponding to the reference quantities in Table B2. As Keeney (1992) emphasizes, these weighting constants are relative to the ranges of outcomes considered. Given that we have calculated unit partial utility values for a particular system—set of reference quantities—we would like to be able to rescale these values for any system without having to reassess decision-maker preferences (and, consequently, recalculate the unit utility factors).

This proposition is facilitated by the assumption of linear single-attribute value (utility) functions over all consequence values. As depicted in Figure 2, let a and b denote the values of attributes A and B. Scaling constants provide a measure of the relative importance of the attributes—relative to their ranges of values. Following the approach of Keeney (1992) and Keeney and Raiffa (1993), suppose attribute A were at its "best" value, a, and attribute B were at its "worst" value, 0. The scaling constant $w_1$ is determined by assessing decision-maker preference indifference, that is, by eliciting the decision-maker to specify a value b that would compensate for a reduction in a to zero. That is, the scaling constant $w_1$ is the slope when the points are connected with a line.

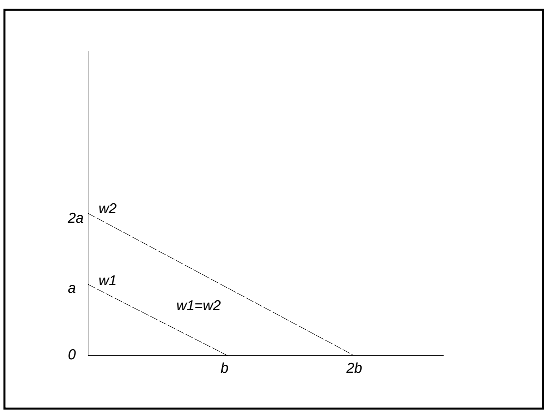


Figure 2. Illustration of Reference Basis Rescaling

As seen in the Figure, these slopes remain constant if both attributes are rescaled by a constant factor, due to our preference assumptions. Similarly, because all of the component utility functions are linear functions of their respective attributes, the unit partial utility factors may be rescaled by a constant factor without the need to reassess decision-maker preferences.

Finally, then, for the actual system that we simulate, we follow the procedure described herein; namely, we estimate "worst case" impacts and determine a scaling factor. And, we multiply all of the unit partial utility factors (Tables B7-B11) by this constant. The actual values used in our simulation model are provided in Table B12.

| Table B12. Unit Partial Utility Factors Used in Simulation | | | | |
|---|---|---|---|---|
| Veh. Type | Utility Factor | Per Mile | Per Minute Engine Idling | Per Engine Start |
| 1 | $u_{HD}$(HD) | -(2.665E-6, 3.970E-6, 5.800E-6) | -(4.405E-7, 6.393E-7, 9.230E-7) | -(4.210E-7, 6.258E-7, 9.053E-7) |
| | $u_{ED}$(ED) | -(3.833E-6, 4.300E-6, 4.918E-6) | -(7.463E-7, 8.228E-7, 9.245E-7) | -(7.168E-7, 8.763E-7, 1.090E-6) |
| | $u_{HP}$(HP) | -(1.523E-6, 4.370E-6, 1.476E-5) | -(6.258E-7, 1.795E-6, 8.753E-6) | -(4.015E-7, 1.152E-6, 5.063E-6) |
| | $u_{EP}$(EP) | -(1.767E-6, 5.693E-6, 1.774E-5) | -(3.853E-7, 1.242E-6, 5.993E-6) | -(2.575E-7, 8.295E-7, 4.330E-6) |
| | $u_R$(R) | -8.320E-06 | -8.955E-07 | -6.133E-07 |
| | $u_O$(O) | -8.630E-06 | -9.105E-08 | -6.250E-08 |
| 2 | $u_{HD}$(HD) | -(3.243E-6, 4.833E-6, 7.050E-6) | -(1.822E-7, 2.753E-7, 3.995E-7) | -(1.235E-7, 1.865E-7, 2.708E-7) |
| | $u_{ED}$(ED) | -(5.210E-6, 5.913E-6, 6.843E-6) | -(2.461E-7, 3.023E-7, 3.775E-7) | -(1.686E-7, 2.070E-7, 2.583E-7) |
| | $u_{HP}$(HP) | -(1.899E-6, 5.448E-6, 1.784E-5) | -(8.180E-8, 2.347E-7, 6.928E-7) | -(5.613E-8, 1.610E-7, 4.750E-7) |
| | $u_{EP}$(EP) | -(2.239E-6, 7.215E-6, 2.230E-5) | -(9.038E-8, 2.913E-7, 1.042E-6) | -(6.215E-8, 2.002E-7, 7.140E-7) |
| | $u_R$(R) | -8.215E-06 | -6.783E-08 | -4.710E-08 |
| | $u_O$(O) | -9.155E-06 | -7.143E-09 | -3.573E-09 |
| 3 | $u_{HD}$(HD) | -(4.038E-6, 6.018E-6, 8.778E-6) | -(7.898E-7, 1.143E-6, 1.649E-6) | -(9.730E-7, 1.460E-6, 2.100E-6) |
| | $u_{ED}$(ED) | -(5.960E-6, 6.880E-6, 8.038E-6) | -(1.343E-6, 1.473E-6, 1.647E-6) | -(1.695E-6, 2.232E-6, 2.95E-6) |
| | $u_{HP}$(HP) | -(2.421E-6, 6.948E-6, 2.389E-5) | -(1.260E-6, 3.615E-6, 1.736E-5) | -(9.505E-7, 2.728E-6, 1.296E-5) |
| | $u_{EP}$(EP) | -(2.665E-6, 8.590E-6, 2.808E-5) | -(7.933E-7, 2.558E-6, 1.222E-5) | -(3.758E-7, 1.211E-6, 1.062E-5) |
| | $u_R$(R) | -1.164E-05 | -1.601E-06 | -7.168E-07 |
| | $u_O$(O) | -8.273E-06 | -2.788E-07 | -7.323E-08 |
| 4 | $u_{HD}$(HD) | -(2.179E-5, 3.218E-5, 4.915E-5) | -(7.058E-6, 1.035E-5, 1.600E-5) | -(4.910E-6, 7.188E-6, 1.105E-5) |
| | $u_{ED}$(ED) | -(6.688E-6, 8.505E-6, 1.093E-5) | -(5.578E-7, 6.973E-7, 8.885E-7) | -(5.768E-7, 6.730E-7, 8.015E-7) |
| | $u_{HP}$(HP) | -(1.293E-5, 3.710E-5, 8.068E-5) | -(4.368E-6, 1.253E-5, 2.583E-5) | -(3.768E-6, 1.081E-5, 3.230E-5) |
| | $u_{EP}$(EP) | -(6.210E-6, 2.001E-5, 7.015E-5) | -(1.845E-6, 5.943E-6, 1.871E-5) | -(1.344E-6, 4.333E-6, 1.949E-5) |
| | $u_R$(R) | -7.630E-06 | -1.053E-06 | -7.153E-07 |
| | $u_O$(O) | -8.953E-06 | -9.825E-08 | -6.608E-08 |

APPENDIX C: VALUES OF ASSUMED DECISION-MAKER FACTUAL- AND VALUE-BASED SCALING CONSTANTS USED IN CALCULATIONS

**Calculated Values of USES-LCA "Eco-Toxic Potential" Damage Indicator**

**Table C1. Calculated USES-LCA Eco-Toxic Damage Potential (ETP) Indicator Values ($D_{ij}$)**

| Stressor | Indicator Value | Defuzzified Value |
|---|---|---|
| (NM)VOC | (1.4E-4, 2.9E-4, 6.3E-4) | 3.5E-4 |
| 1,3-Butadiene | (8.2E-7, 1.7E-6, 3.6E-6) | 2.0E-6 |
| Formaldehyde | (9.0E-1, 2.6E+0, 6.5E+0) | 3.3E+0 |
| Toluene | (1.8E-4, 3.8E-4, 8.2E-4) | 4.6E-4 |
| Benzene | (5.9E-4, 1.2E-3, 2.5E-3) | 1.4E-3 |
| Acetaldehyde | (1.4E-4, 2.9E-4, 6.3E-4) | 3.5E-4 |
| MTBE | (1.4E-4, 2.9E-4, 6.3E-4) | 3.5E-4 |
| DPM-10 | (2.6E+3, 5.2E+3, 1.1E+4) | 6.3E+3 |

Value- and factual-based judgments are ascribed for a single reference substance (1,4-dichlorobenzene):

| Compartment | $b_k$ | $w_k$ |
|---|---|---|
| Terrestrial | (0.3, 0.5, 0.7) | 0.2 |
| Fresh water aquatic | (0.1, 0.3, 0.5) | 0.2 |
| Marine aquatic | (0.5, 0.7, 0.9) | 0.2 |
| Fresh water sediment | (0.1, 0.3, 0.5) | 0.2 |
| Marine sediment | (0.5, 0.7, 0.9) | 0.2 |

Values of $ETP_i$ are calculated as:

$\boldsymbol{ETP}_i = \sum_k [(w_k \boldsymbol{b}_k D_{ik}) / (\sum_k w_k \boldsymbol{b}_k)]$,

where $D_{ik}$ is the compartment- and substance-specific ecological toxicity indicator value.

**Assumed Weighting Constants for Calculation of Human Health and Ecological Potential Damage, $u_{HD}$(HD) and $u_{ED}$(ED)**

| Table C2. Normalized Values of $b_{Xlijk}$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Human Health Damage Category** | | | | | | **Ecological Damage Category** | |
| | GLOBAL WARMING | | HUMAN TOXICITY | | OXIDANT FORMATION | | SPECIES LOSS | |
| Stressor | EPS-CDALY | Eco-In. DALY | EPS-CDALY | Eco-In. DALY | EPS-CDALY | Eco-In. DALY | EPS-NEX | Eco-In. PDF |
| $CO_2$ | (.38, .55, .78) | (.31, .45, .67) | | | | | (1, 1, 1) | (0, 0, 0) |
| CO | (1, 1, 1) | (0, 0, 0) | (.38, .55, .78) | (.31, .45, .67) | | | (1, 1, 1) | (0, 0, 0) |
| $NO_x$ | (1, 1, 1) | (0, 0, 0) | (.40, .58, .90) | (.27, .42, .60) | (1, 1, 1) | (0, 0, 0) | (.43, .64, 1.0) | (.21, .36, .56) |
| PM-10 | (1, 1, 1) | (0, 0, 0) | (.40, .58, .90) | (.27, .42, .60) | | | (1, 1, 1) | (0, 0, 0) |
| (NM)VOC | (1, 1, 1) | (0, 0, 0) | | | (.33, .50, .75) | (.33, .50, .75) | (1, 1, 1) | (0, 0, 0) |
| $SO_x$ | (1, 1, 1) | (0, 0, 0) | (.40, .58, .90) | (.27, .42, .60) | | | (.43, .64, 1.0) | (.21, .36, .56) |
| 1,3-Butadiene | (1, 1, 1) | (0, 0, 0) | (.21, .36, .56) | (.43, .64, 1.0) | (.21, .36, .56) | (.43, .64, 1.0) | (1, 1, 1) | (0, 0, 0) |
| Formaldehyde | (1, 1, 1) | (0, 0, 0) | (.21, .36, .56) | (.43, .64, 1.0) | (.21, .36, .56) | (.43, .64, 1.0) | (1, 1, 1) | (0, 0, 0) |
| Toluene | (1, 1, 1) | (0, 0, 0) | | | (.21, .36, .56) | (.43, .64, 1.0) | (.40, .58, .90) | (.27, .42, .60) |
| Benzene | (1, 1, 1) | (0, 0, 0) | (.31, .45, .67) | (.38, ,55, .78) | (.31, .45, .67) | (.38, ,55, .78) | (.40, .58, .90) | (.27, .42, .60) |
| Acetaldehyde | (1, 1, 1) | (0, 0, 0) | (0, 0, 0) | (1, 1, 1) | (.31, .45, .67) | (.38, ,55, .78) | (1, 1, 1) | (0, 0, 0) |
| CH4 | (.38, .55, .78) | (.31, .45, .67) | | | (.40, .58, .90) | (.27, .42, .60) | (1, 1, 1) | (0, 0, 0) |
| MTBE | (1, 1, 1) | (0, 0, 0) | | | (.21, .36, .56) | (.43, .64, 1.0) | (1, 1, 1) | (0, 0, 0) |
| DPM-10 | (1, 1, 1) | (0, 0, 0) | (.43, .64, 1.0) | (.21, .36, .56) | (0, 0, 0) | (1, 1, 1) | (.45, .67, 1.17) | (.09, .33, .67) |

**Assumed Weighing Constants for Calculation of Human Health and Ecological Damage Potential**

| **Table C3. Values of Value- and Factual-Based Scaling Constants $c_{Xj}$, $\boldsymbol{d}_{Xj}$, $\boldsymbol{e}_{Xjk}$, and $h_{Xjk}$** | | | |
|---|---|---|---|
| Attribute (Objective) | Component Attribute or Constituent LCIA Indicator | Scaling Constant | Value |
| Human Health Damage Potential (HP) | Global Warming Damage Potential (GWDP-H) | $c_{H1}$ | 0.47 |
| | | $\boldsymbol{d}_{H1}$ | (0.25, 0.5, 0.75) |
| | Human Toxicity Damage Potential (HTDP) | $c_{H2}$ | 0.30 |
| | | $\boldsymbol{d}_{H2}$ | (0.5, 1, 1) |
| | Oxidant Creation Damage Potential (OCDP-H) | $c_{H3}$ | 0.23 |
| | | $\boldsymbol{d}_{H3}$ | (0, 0, 0.5) |
| Ecological Damage Potential (EP) | Global Warming Damage Potential (GWDP-E) | $c_{E1}$ | .34 |
| | | $\boldsymbol{d}_{E1}$ | (0.5, 1, 1) |
| | Eco-Toxicity Damage Potential (ETDP) | $c_{E2}$ | 0.22 |
| | | $\boldsymbol{d}_{E2}$ | (0.25, 0.50, 0.75) |
| | Oxidant Creation Damage Potential (OCDP-E) | $c_{E3}$ | 0.12 |
| | | $\boldsymbol{d}_{E3}$ | (0, 0, 0.5) |
| | Acidification Damage Potential (ADP) | $c_{E4}$ | 0.17 |
| | | $\boldsymbol{d}_{E4}$ | (0, 0, 0.5) |
| | Eutrophication Damage Potential (EDP) | $c_{E5}$ | 0.15 |
| | | $\boldsymbol{d}_{E5}$ | (0, 0, 0.5) |
| Human Toxicity Damage Potential (HTDP) | USES-Human Toxicity Potential (USES-HTP) | $h_{H21}$ | 0.50 |
| | | $\boldsymbol{e}_{H21}$ | (0.5, 1, 1) |
| | USEPA Human Health Hazard Ranking Factor (EPA-HHHRF) | $h_{H22}$ | 0.50 |
| | | $\boldsymbol{e}_{H22}$ | (0, 0, 0.5) |
| Eco-Toxicity Damage Potential (ETDP) | USES Eco-Toxicity Potential (USES-ETP) (Constructed Attribute) | $h_{E21}$ | 0.78 |
| | | $\boldsymbol{e}_{E21}$ | (0.5, 1, 1) |
| | USEPA Terrestrial Hazard Ranking Factor (EPA-THRF) | $h_{E22}$ | 0.11 |
| | | $\boldsymbol{e}_{E22}$ | (0, 0, 0,5) |
| | USEPA Aquatic Hazard Ranking Factor (EPA-AHRF) | $h_{E23}$ | 0.11 |
| | | $\boldsymbol{e}_{E23}$ | (0, 0, 0.5) |

**Assumed Weighting Constants for Calculation of Ecological Potential Damage, Human Health Damage, Ecological Damage, Resource Depletion, Other Impacts, and Highest-Level Utility Function**

**Table C4. Values of Remaining, Assumed (Hypothetical) Value-Based Scaling Constants**

| Utility Function (Attribute) | Component Attribute | Scaling Constant | Value |
|---|---|---|---|
| Ecological Potential Damage (ED) | Species Loss | $w_{E1}$ | 0.59 |
| | Productive Capacity Loss | $w_{E2}$ | 0.28 |
| | Soil Base Cation Capacity Loss | $w_{E3}$ | 0.13 |
| Resource Depletion | Base Metal Depletion | $w_{R1}$ | 0.10 |
| | Precious Metal Depletion | $w_{R2}$ | 0.30 |
| | Non-Renewable Energy Consumption | $w_{R3}$ | 0.60 |
| Other Impacts | TRI Emissions | $w_{O1}$ | 0.55 |
| | Solid (non-RCRA) Waste Generation | $w_{O2}$ | 0.15 |
| | RCRA Waste Generation | $w_{O3}$ | 0.30 |
| Human Health Damage (H) | Human Health Potential Damage (HD) | $w_{H11}$ | 0.88 |
| | Human Health Damage Potential (HP) | $w_{H12}$ | 0.34 |
| Ecological Damage (E) | Ecological Potential Damage (ED) | $w_{E11}$ | 0..84 |
| | Ecological Damage Potential (EP) | $w_{E12}$ | 0.49 |
| Environmental Impact (Highest-level objective) | Human Health Damage (H) | $w_H$ | 0.47 |
| | Ecological Damage (E) | $w_E$ | 0.23 |
| | Resource Depletion (R) | $w_R$ | 0.17 |
| | Other Impacts (O) | $w_O$ | 0.13 |

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