Jointly Optimizing Cost, Service, and Environmental Performance in Demand-Responsive Transit Scheduling

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ABSTRACT

In certain types of fleet systems, the environmental impacts of fleet operation are, to some extent, a controllable function of vehicle routing and scheduling decisions. However, 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 methodologies such as those described by the Society of Environmental Chemistry and Toxicology. In this paper, we present a methodology 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. We demonstrate through simulation that, as a result of our methodology, it is possible to reduce environmental impacts substantially, while increasing operating costs and service delays only slightly.

KEYWORDS:

paratransit, dial-a-ride, life cycle analysis (LCA), life cycle impact assessment (LCIA), routing and scheduling, optimization

1. INTRODUCTION

At the present time, over 100 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 (NO_2), sulfur dioxide (SO_2), ozone (O_3), lead (Pb), and particulate matter (PM-10). Transportation is a significant contributor to these air quality problems. According to the United States Environmental Protection Agency (USEPA 1999), about two-thirds of all CO emissions, and about one-third of all emissions of NO_2 and volatile organic compounds (VOCs), nation-wide, 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, hexane, acetaldehyde, styrene, toluene, and xylene. For these specific substances, highway vehicles are responsible for about one-quarter to one-half of total U.S. emissions, depending upon the pollutant. 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.

The environmental impacts of transportation are even more significant when examined on a life-cycle basis. When examined on this basis, it is 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, "zero emitting" electric vehicles transfer emissions from the tailpipe to the electric utility; and, the much heralded fuel cell requires a hydrogen source that must be produced and distributed by some means, resulting in environmental impacts. Even with cleaner fuels, other aspects of transportation system design and operation must also be addressed if overall or life-cycle environmental impacts are to be minimized.

Among public and private vehicle fleet operations many utilize a heterogeneous vehicle fleet, comprised of vehicles having different capacities or capabilities. Assuming that the different vehicle types or sizes have correspondingly different environmental impacts, the controllable environmental impacts of operation are affected by vehicle assignment and/or scheduling decisions. The vehicle assignment and routing that minimizes the transit distance or cost of servicing a particular demand may not be the assignment and routing that minimizes the environmental impacts of servicing the demand. In other words, from the perspective of servicing a demand where multiple vehicle assignments and routings are available, the variables of route distance, cost, and environmental impacts may be uncorrelated. Moreover, the environmental impacts may be a function of variables in addition to travel distance alone. Thus, the joint optimization of cost, service, and environmental impact variables is a multi-objective problem. By including environmental impacts in the scheduling optimization function, these impacts can be optimized (minimized) jointly with other decision variables.

The dispatching of vehicles in fleet operations entails the assignment of vehicles to routes, the ordering of stops (nodes) within a route, or a combination of the two. 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 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 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. Our testbed is based on dial-a-ride service in Los Angeles County, which has one of the largest such programs and is representative of other programs in the country. In the U.S., the Americans with Disabilities Act (ADA) requires municipal transit operators to accommodate disabled patrons. 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. According to Simon (1998), "ADA paratransit services have become the fastest growing segment of public transit ridership … costing the transit industry as much as $1 billion annually in operating funds." In 1996, 95.4 million demand-responsive (paratransit) trips were served by public and private paratransit services in the U.S., compared to 68 million in 1990. The number of private companies providing paratransit services also has grown significantly, from 6,300 providers operating over 200,000 vehicles in 1986 to 22,884 providers operating over 370,000 vehicles in 1998 (Lave and Mathias 2000). Paratransit patrons include both those requiring wheelchair accommodation and those that do not. For this and other reasons (such as time-variant demand), a paratransit fleet may be comprised of multiple types or capacities of vehicles. For example, a study by Simon (1998) found that the majority of surveyed paratransit providers utilized a fleet comprised of two or more types of vehicles.

1.1. Environmental Life-Cycle Analysis

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 1991, 1993) is generally credited for the current LCA methodological framework. Recent standards by the International Organization for Standardization (i.e., 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. In the case of transportation vehicles, relevant life-cycle stages include not only vehicle operation, but also stages of vehicle production, the production of components and materials used in vehicle maintenance as well as the maintenance activity itself, and the "fuel cycle"—the extraction, refining, and distribution of motor fuels—to name just a few. The impacts in these other life-cycle stages may be significant. DeLuchi (1993) found that VOC, NO_2, and SO_2 emissions from the "fuel cycle" to be comparable to those from the tailpipe on a normalized or "per mile" basis. From this analysis, it is clear that the reduction of transportation environmental impacts requires consideration of the impacts over all life-cycle stages.

1.2. 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. There has also been limited prior work in the area of multi-objective network optimization, including that based on environmental impacts (tailpipe emissions). In general, this research (e.g., Benedek and Rilett 1998; Shaheen, et al. 1998) has focused on optimization of vehicle routing based on various traffic assignment principles and algorithms. Individual vehicles were assigned routings on simulated traffic networks 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. 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, e.g., Sommerville and Bostock 1994 and Taylor and Herbert 1993.)

Insofar as the problem of fleet vehicle routing and scheduling 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. 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.

2. PARATRANSIT LIFE-CYCLE MODEL

We consider a paratransit fleet 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 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. 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.

Figure 1 here

Vehicle running emissions are modeled utilizing the California Air Resource Board (1998, 2000) EMFAC/Burden model. This is a regional emissions inventory model. 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 and representing a typical "drive cycle." (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 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. The results of our life-cycle inventory analysis, with impacts summed over all life-cycle stages, are presented as Table 1.

Table 1 here

3. LIFE-CYCLE IMPACT ASSESSMENT BASIS

From a decision-theoretic perspective (e.g., Keeney 1988, 1992), it is the consequences (e.g., human health damages) of the environmental impacts, rather than the impacts themselves, that are the basis for concern and the appropriate basis for optimization. This is also consistent with the overall SETAC 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 impact(s) 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 bioaccumulation (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. 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 considered in the analysis. An informative overview of current LCA and LCIA practice may be found in Curran (ed. 1996).

From both the practical and theoretical perspectives, there are many contemporaneous issues associated with these LCIA methods. Among these are the imprecise relationship between LCIA results and actual damages that may be accrued (e.g., Besnainou and Coulon 1996; Owens 1997, 1999) and the question of 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 (Notarnicola, et al. 1998). Additionally, many of the methods provide formulas for valuation or prescriptions for decision-making,some of which are dubious from a decision-theoretic perspective (Or: Some of these prescriptions are dubious …) (Miettinen and Hämäläinen 1997; 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 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.

3.1. Selection of Proxy Attributes for Human Health and Ecological Damages

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, 1999b); Eco-Indicator (Goedkoop and Spriensma 2000a, 2000 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 (1999). Also included in the Tables are potentials (equivalency factors) for global warming, photochemical oxidant creation, and acidification (Centre of Environmental Science 2001, United States Environmental Protection Agency 1996b) as well as hazard scores for human, aquatic, and terrestrial toxicity, based on the United States Environmental Protection Agency's (1994) hazard assessment methodology. The indicators were selected to include both end-point and mid-point damages. While the final form and appearance of our decision model are predicated on the selected indicators, other indicators could have been utilized just as well. 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.

Tables 2, 3 here

Several important points should be noted. First, the values shown in the Tables 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 weighting or normalization factors. We develop our own weighting factors for the decision model that we develop. Second, as explained in the notes accompanying the Tables, we have combined the certain EPS damage indicators into a single constructed attributes ("Calculated Disability-Adjusted Life-Years" [CDALYs] and "Productive Capacity Losses") following an approach developed by Murray and Lopez (1996, reported in Goedkoop and Spriensma 2000a). However, we would have had to perform such aggregation at some other stage of the decision model evaluation if we had not done so here. Third, we follow Besnainou and Coulon's (1996) and Owens' (1997, 1999) view that the damage indicators provided by the previous LCIA methods provide performance indicators, rather than precise predictions of actual damages that will be accrued. As such, following Keeney's (1992) terminology, decision attributes defined based on these indicators are "proxy attributes." Finally, the stressors identified in Table 1 include certain resource consumptions and other impacts (e.g., RCRA and solid wastes) for which data is not provided in Tables 2 and 3 because we use these impacts and quantities directly as attributes in the decision model.

4. DECISION-THEORETIC BASIS AND MODEL

For the reasons discussed previously, we utilize the data (damage indicators) from multiple methods and levels of analysis in our decision model, as suggested by Bare, et al. (2000). We note 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. We do not wish to alter the various methods' impact categories, damage functions and indicators, and internal stressor and damage allocations.

Because there is no scientific basis by which to combine multiple consequences (e.g., human health and ecological damage) into a single measure (other than desirability) by which to identify the best alternative, and to maintain consistency with current LCIA methods, we choose utility theory (e.g., Fishburn 1964, 1970; Keeney and Raiffa 1993) as the basis on which to develop our decision model.

Following the SETAC LCA framework, 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 for which consequence data is unavailable. As suggested by Bare, et al. (2000), we consider both mid-point and end-point indicators for the human health and ecological categories; and, we specify these as sub-objectives. The basic decision model as developed is shown in Figure 2, where the relationship between objectives and attributes (LCIA damage indicators from Tables 2 and 3) is also shown. The w_i's are preference-based weighting or scaling constants. Also, we have combined Huijbregts, et al.'s (2000) various ecological toxic potential indicators (from Table 3) into a single constructed attribute, Eco-Toxicity Potential, following an approach that we describe later.

Figure 2 here

We proceed by first illustrating the formulation of a decision model based on damage indicators from a single LCIA method (EPS for purposes of illustration). Then, we illustrate its modification to include damage indicators from additional end-point (potential damage) LCIA methods. Finally, we develop a similar model based on damage indicators from multiple mid-point (damage potential) LCIA methods and, then, combine the two models into a single model. Before we can do this, we must address the problem of "uncertainty" that is frequently noted in the LCA literature, specifically, the uncertainty relating LCIA results (as proxy attributes) to actual environmental damages.

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

Following the convention of current LCIA methods, we assume that single-attribute (unidimensional) utility functions have a constant rate of (utility) substitution, i.e., are linear. For example, let D_j denote the value of (damage) attribute j. Then,

$$u(D_j) = - [D_j - D_{j(BEST)}] / [D_{j(WORST)} - D_{j(BEST)}], \quad (1)$$

where $D_{j(WORST)}$ and $D_{j(BEST)}$ denote the "worst" and "best" values of attribute j, respectively, among the alternatives considered and $u(D_j)$ is a utility function for values of attribute D_j. Note that we have defined the utility scale such that 0 is "best" and –1 is "worst." However, in our 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 scenarios. We define $D_{j(BEST)} = 0$ and redesignate $D_{j(WORST)}$ as D_{jREF}. Then,

$$u(D_j) = - D_j / D_{jREF}. \quad (2)$$

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:

$$D_j = \sum_i I_i D_{ij} = \sum_i \sum_k I_i D_{ijk}, \quad (3)$$

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. 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 the United States Environmental Protection Agency (1994) methodology.

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

$$u(x_1, x_2, \ldots, x_n) = f[u_1(x_1), u_2(x_2), \ldots, u_n(x_n)], \quad (4)$$

where the actual form of $f[u_i(x_i)]$ is predicated upon whether certain preference independence conditions (among attributes) are met. 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 (only) as recommended by Keeney and Raiffa (1993), including the nesting of such forms within a larger overall model. Mathematically, these are expressed, respectively, as:

$$u(x_i) = \sum_i w_i\, u_i(x_i), \text{ where } \sum_i w_i = 1, \text{ and} \tag{5}$$

$$Ku(x_1, x_2, \ldots, x_n) + 1 = \prod_i^n [Kk_i u_i(x_i) + 1]. \tag{6}$$

If there were only two objectives, for example, it can be seen that the multiplicative form reduces to:

$$u(x_1, x_2) = w_1 u_{X1}(x_1) + w_2 u_{X2}(x_2) + (1 - w_1 - w_2) u_{X1}(x_1) u_{X2}(x_2). \tag{7}$$

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:

$$u(\text{itinerary}) = f[u_H(H), u_E(E), u_R(R), u_O(O)], \tag{8}$$

where

$$u_H(H) = f[u_{HD}(HD), u_{HP}(HP)] \tag{9}$$

$$u_E(E) = f[u_{ED}(ED), u_{EP}(EP)]. \tag{10}$$

Following current LCIA practice, we assume the highest-level attributes of Equation 8 to be additive independent. We also see this assumption as reasonable for the aggregation of attributes within 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 that a decision-maker's preference for the values of one set of attributes is not (additive) independent of the other set of attributes. Thus, 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:

$$u(\text{itinerary}) = w_H\, u_H(H) + w_E\, u_E(E) + w_R\, u_R(R) + w_O\, u_O(O), \text{ where} \tag{11}$$

$$u_H(H) = w_{HD}\, u_{HD}(HD) + w_{HP}\, u_{HP}(HP) + (1-w_{HD}-w_{HP})\, u_{HD}(HD)u_{HP}(HP), \tag{12}$$

$$u_E(E) = w_{ED}\, u_{ED}(ED) + w_{EP}\, u_{EP}(EP) + (1-w_{ED}-w_{EP})u_{ED}(ED)u_{EP}(EP), \tag{13}$$

where $w_H + w_E + w_R + w_O = 1$ and all other terms are as defined previously.

4.2. Treatment of Proxy Attributes and Factual Judgments Utilizing Fuzzy Linguistic Variables

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 and value-based judgments. These problems become acutely relevant when we combine damage indicators from multiple LCIA methods because the underlying models from which the damage indicators are derived are not identical and consider different intermediate impact categories, damage functions, etc. Thus, in order to combine damage indicators 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.

We assume that the decision-maker can make the necessary value-based judgments on a precise or scalar basis, following utility theory and LCIA practice. However, according to Keeney (1992), the problem that arises results from the combination or intermingling of the required value- and factual based judgments. He provides an approach wherein the judgments are decoupled and the factual-based judgments are made on a probabilistic basis. While Keeney's (1992) 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. We also implicitly assume that the requisite utility theory axioms concerning probabilistic outcomes hold for possibilistic outcomes, as well.

Figure 3 provides an example problem that we utilize to derive and illustrate our methodology. In the Figure, we wish to evaluate a utility function, u(Ecological Damage), comprised of two objectives: (actual) Crop Damage and (actual) Species Loss, denoted at D_1 and D_2. For illustration, we utilize the EPS damage indicators Productive Capacity Loss and NEX, respectively, as measures of these damages. Also for illustration, we assume that the utility function and damage indicators are evaluated for an alternative involving a single stressor. Lastly, we evaluate the utility function based upon an assumed linear-additive preference decomposition form.

Figure 3 here

Let y_1 and y_2 denote proxy attributes for actual consequences (damage potentials or potential damages) D_1 and D_2, where $D_1=f_1(y_1)$ and $D_2=f_2(y_2)$. The functions f_1 and f_2 are functions relating proxy attribute values to actual damages. The problem is that f_1 and f_2 are not known and can be assessed only on a vague (fuzzy) rather than probabilistic basis. Now, suppose we specified a utility function such that:

$$u(D_1, D_2) = [w_1u(D_1) + w_2u(D_2)]/(w_1+w_2) \tag{14}$$

$$= [w_1(-D_1/D_{1REF}) + w_2(-D_2/D_{2REF})]/(w_1+w_2) \tag{15}$$

$$= \{-w_1[f_1(y_1)/f_1(y_{1REF})] - w_2[f_2(y_2)/f_2(y_{2REF})]\}/(w_1+w_2). \tag{16}$$

Although f_1 and f_2 are not known, from LCIA convention, $f_1(0) = 0$, $f_2(0) = 0$, and f_1 and f_2 are monotonically increasing. Thus, it is reasonable to approximate them as general power functions of the form $f(y) =ay^b$, where a and b are positive-valued constants, and $f(y)/f(y_{REF}) \approx f(y/y_{REF})$.

Now, let $\boldsymbol{D}_1 = \boldsymbol{b}_1{*}y_1$, $\boldsymbol{D}_2 = \boldsymbol{b}_2{*}y_2$, $\boldsymbol{D}_{1REF} = \boldsymbol{b}_1{*}y_{1REF}$, and $\boldsymbol{D}_{2REF} = \boldsymbol{b}_2{*}y_{2REF}$, where $\boldsymbol{b}_1{*}$ and $\boldsymbol{b}_2{*}$ are linguistic variables represented by normal, triangular fuzzy numbers of the form (l, m, u) where $l \le m \le u$ and $l \ge 0$, assessed utilizing factual judgments about D_1 and D_2 based upon y_1 and y_2. (Notationally, fuzzy variables are denoted using bold-italic typeface.) Then,

$$\boldsymbol{u}(D_1, D_2) = \{-w_1[(\boldsymbol{b}_1{*}y_1)/(\boldsymbol{b}_1{*}y_{1REF})] - w_2[(\boldsymbol{b}_2{*}y_2)/(\boldsymbol{b}_2{*}y_{2REF})]\}/(w_1+w_2) \tag{17}$$

$$= \{-w_1\boldsymbol{b}_1(y_1/y_{1REF}) - w_2\boldsymbol{b}_2(y_2/y_{2REF})\}/(w_1 + w_2), \tag{18}$$

where

$$\boldsymbol{b}_i = (\boldsymbol{b}_i^*/\boldsymbol{b}_i^*) \approx (\min[l_i/l_i,\ l_i/u_i,\ u_i/u_i,\ u_i/l_i],\ m_i/m_i,\ \max[l_i/l_i,\ l_i/u_i,\ u_i/u_i,\ u_i/l_i]) \quad (19)$$

$$= (l_i/u_i,\ 1,\ u_i/l_i) \quad (20)$$

The extension of the above to more than two objectives is straight-forward:

$$\boldsymbol{u}(D_1, D_2, \ldots, D_n) = [\textstyle\sum_{i=1}^{n} w_i \boldsymbol{b}_i(-y_i/y_{iREF})], \quad (21)$$

where, in this case, the w_i values have been normalized; that is, $\sum_i w_i = 1$.

The $\boldsymbol{b}_i$ values that we utilize are "normalized" values in the above sense, that is, $\sum_{i=1}^{I} w_i \boldsymbol{b}_i = (a, 1, c)$. As a consequence, the resultant utility function is scaled 0 to "about –1," where, for example, the defuzzified (scalar) value of $u(D_{jREF}/D_{jREF})$ may be more or less than –1 depending upon the defuzzification algorithm that is used. The $\boldsymbol{b}_i$ terms are assessed or evaluated by the decision-maker in consideration of the underlying LCIA models and modeled damages and damage functions. Specifically, the $\boldsymbol{b}_i^*$'s are assessed utilizing linguistic variables, which are represented as normal, triangular fuzzy numbers, for example, "very low" ≡ (0, 0, 0.3), "high" ≡ (0.5, 0.7, 0.9), etc. Or, the $\boldsymbol{b}_i$'s can be assessed directly (i.e., on a relative basis). For example, the decision-maker may feel that the actual species loss per unit value of the EPS NEX indicator is "much greater" than the actual crop damage per unit EPS Lost Productive Capacity indicator. The point is that the $\boldsymbol{b}_i$'s or $\boldsymbol{b}_i^*$'s represent the imprecision between proxy attribute and actual damages, which may be different among different attributes and damages.

A similar procedure is utilized for evaluation of constructed proxy attributes. Specifically, we combine Huijbregts, et al.'s (2000) various ecological toxicity potentials (Table 3) into a single unit damage indicator, Eco-Toxicity Potential, which we will then utilize as a proxy attribute. The important difference in this case is that we are evaluating a constructed attribute and not a utility function. In the derivation presented previously, we were interested in evaluating a utility function comprised of two objectives, D_1 and D_2, which were evaluated based upon proxy attributes y_1 and y_2 (Equation 17). It should be seen that we were not interested in the values of D_1 and D_2, only of $u(D_1)$ and $u(D_2)$. We are not determining the value of an attribute D' such that $u(D') = -D'/D'_{REF}$. In the case of Ecological Toxicity

Potential, we are determining the value of the constructed attribute (unit damage indicator) denoted as D_{ij}. From the subscript (i), it should be seen that we are evaluating D_{ij} for each substance (stressor) i. We are not, at this point, evaluating $u(D_{ij})$, although we wish to specify D_{ij} in such a way that we can, later, determine $u(D_{ij})$ following our overall methodological approach and preference assumptions.

We calculate the unit damage indicator, Ecological Toxicity Potential (USES-ETP), denoted as D_{ij}, value for each substance i listed in the LCI (Table 1), as

$$\boldsymbol{D}_{ij} = \sum_k [(w_k \boldsymbol{b}_k D_{ijk}) / (\sum_k w_k \boldsymbol{b}_k)], \quad (22)$$

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 3). We then defuzzify the $\boldsymbol{D}_{ij}$ values for subsequent use as unit damage indicator values. The primary difference between this result and Equation 21 is that in this case, the value that we are calculating is actually a weighted average. Finally, we note that in Huijbregts, et al.'s (2000) methodology, toxicity potentials are calculated based on a single reference substance (1,4-dichlorobenzene), and only one $\boldsymbol{b}_k$ based on 1,4-dichlorobenze is assessed for each damage compartment.

4.3. 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 do not assign the stressors identically to the same impact categories. Hence, the resultant indicators, e.g., for species loss (NEX and PDF, respectively), are not comparable measures. In other words, decision-maker must make factual judgments insofar as the magnitude of actual damages represented by each proxy measure on a stressor-by-stressor basis, unlike the previous example aggregating Huijbregts, et al.'s (2000) ecological toxicity potentials. The solution approach, in this case, is found by combining Equations 2 and 3.

$$u(D_j) = - [\sum_i I_i D_{ij} / D_{jREF}] = \sum_i u(D_{ij}), \quad (23)$$

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.

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. 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:

$$\boldsymbol{u}_{Xli}(a_{Xli}) = - \sum_j \{I_i \sum_k [(D_{ijk})(\boldsymbol{b}_{Xlijk})] / D_{j(REF)}\}, \qquad \forall\ D_j \in A_{Xl} \qquad (24)$$

where the $\boldsymbol{b}_{Xlijk}$ values are normalized values representing factual judgments as to the relative significance associated with each damage indicator D_{ijk}, evaluated for each damage type j and stressor i. Additionally, it can be seen in Equation 24 that there are no value-based scaling constants involved (only the factual-based scaling constant $\boldsymbol{b}_{Xlijk}$) because we are aggregating damage indicators that provide measures of the same (actual) damage, a_{Xli}. Finally, the partial utility values are then aggregated over all stressors as:

$$\boldsymbol{u}_{Xl}(a_{Xl}) = \sum_i \boldsymbol{u}_{Xli}(a_{Xli}), \qquad \text{for } X = \text{HD, ED}. \qquad (25)$$

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

$$\boldsymbol{u}_X(X) = \sum_l w_{Xl}\boldsymbol{u}_{Xl}(a_{Xl}), \qquad l = 1, 2, \ldots ; \sum_l w_{Xl} = 1; \text{ for X=HD, ED}. \qquad (26)$$

In Equation 26, we utilize value-based scaling constants, w_{Xl}, since we are aggregating different damages.

4.4. Evaluation of Mid-Point Damage-Based Utility Functions, $u_{HP}(HP)$ and $u_{EP}(EP)$

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. Specifically, from Figure 2, aggregation steps must be performed at two levels in the objectives hierarchy utilizing Equations 23 through 26. Also, the lower-level attributes are aggregated in the evaluation of both end-point- and mid-point-based utility functions. These could be evaluated by first evaluating a constructed attribute based upon them, as we did in the case of Eco-toxicity Potential using Equation 22, and then evaluating a single-attribute utility function utilizing the constructed attribute and Equation 2. Alternatively, utility functions based upon the lower-level damage indicators may be evaluated directly utilizing Equations 23 through 26. In deciding between the two approaches, we evaluated Eco-toxicity

Potential separately, as a constructed attribute, to reduce the number of comparative factual judgments the decision-maker had to make in any one evaluation step.

The most important difference in the evaluation of mid-point damage-based utility functions is that the value- and factual-based scaling constants are not assessed for each stressor i. 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.

4.5. Evaluation of Resource Depletion and Other Impacts Utility Functions, $u_R(R)$ and $u_O(O)$

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. Utility values are calculated by simply substituting the LCI quantity (I_i) for I_iD_{ij}, and I_{iREF} for D_{jREF}, in Equation 23 (and changing summation indices accordingly), because, in the case of these utility functions, there is a one-to-one relationship between the stressor and the damage indicator.

4.6. 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. 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 3). The itinerary utility value (Equation 11) is calculated utilizing the utility relationships described in the preceding sections. It should be seen that certain of the calculated intermediate quantities are (normal, triangular) fuzzy numbers, which must be defuzzified in order to facilitate ranking or comparison. For this purpose, we use the common Center of Area (COA) defuzzification algorithm (see, for example, Klir and Yuan 1995), which returns the support (x- or abscissa) value of the centroid of the fuzzy possibility distribution.

Finally, in Equations 11– 13, because of the existence of the multiplicative utility functions, the resultant itinerary utility value cannot be on a scale of 0 to "about –1" unless the values of the multiplicative scaling constants, e.g., ($1-w_{HD}-w_{HP}$), are zero. One solution to this, suggested by Keeney and Raiffa (1993), is to rescale the respective utility functions based upon the values of the scaling constants. Alternatively, it should be recognized that the 0 to –1 scale is not mandatory and that any scale may be utilized so long as the affected scaling constants are assessed over the same scale basis. We chose the latter approach to leave the decision model generic and to avoid having to rescale the affected utility functions for each simulation scenario.

5. PARATRANSIT OPERATIONS

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 immediate-service (same-day or "ASAP") 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.

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 if they refuse "appropriate" service requests or miss agreed upon time windows. 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.

5.1. Paratransit Vehicle Scheduling

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 Jaw, et al. (1986) and Psaraftis (1980), the paratransit problem of interest is a "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 (1980) 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. 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. Their solution also 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; Solomon, 1987; 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-schedule (post-insertion) optimization procedures (e.g., Gendreau, et al., 1992, 1994), applicable to itineraries constructed using insertion-type as well as other algorithms.

5.2. Modeled Paratransit System and Operation

We demonstrate the methodology through computer simulation of a paratransit system operation, where the modeled system is based on that of San Gabriel Transit, an ACCESS Services (paratransit) provider in Los Angeles County. 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. The fleet is comprised of different types and sizes (capacities) of vehicles. Two types of requests are provided for, immediate and advance. Advance requests are scheduled at the beginning of the shift (the first shift on which they could be serviced.) 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. 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, 1998b). Experimental values of these and the previous parameters are provided in Table 4.

Simulated vehicle operation is governed by certain service polices, including those affecting engine starts and engine idling. Specifically, 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 to allow for operation of the vehicle's air conditioner or heater as well as other devices, in accordance with ACCESS Services [2000] contractual terms that require the vehicle to be maintained at a comfortable temperature.) 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.)

5.3. Real-Time Scheduling Heuristic

To demonstrate the methodology, we adapt Jaw, et al.'s (1986) heuristic, parallel insertion algorithm to the modeled service policies and penalties described above. However, the specific algorithm chosen is not critical to our purpose or result. We first consider the algorithm based solely on "traditional" (economic) costs; and, we then modify it to include environmental impacts. Specifically, we consider an objective function including transit- (distance-) related cost as well as economic penalties imposed if the vehicle arrives early or late (outside of the "on-time" window) at a pick-up location. The algorithm works by constructing itineraries for multiple vehicles in parallel, tentatively "inserting" the request into each vehicle's itinerary. The best insertion is the one that minimizes the (economic) cost of servicing the request.

We next modify the previous heuristic to include environmental impacts. 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:

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

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 $\sum_{i\in R} u(CS_i, EC_i)$.

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

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

5.4. Experimental Design

To facilitate evaluation of the previous equations and demonstrate the methodology, we have assumed values for all of the previous factual- and value-based scaling constants for a hypothetical decision-maker. For brevity, we omit these; however, values of experimental and other cost/service parameters are provided in Table 4. (For the omitted values as well as additional details concerning the decision methodology and optimization procedure, the reader is referred to Dessouky, Rahimi, and Weidner 2002.) Also for brevity, we only discuss the experimental design 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.

We consider several fleet composition scenarios. 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. We also simulate various levels of system loading by adjusting the number of available vehicles. Specifically, we would expect to find greater environmental improvement in a system having excess vehicles (including "environmentally friendlier" ones) available. 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 to facilitate the comparison of results on a paired basis.

Table 4 here

6. EXPERIMENTAL RESULTS

Results, for the fleet compositions and sizes (representing different levels of system loading) simulated, are provided in Tables 5 through 8. In the tables, the first row of each composition-size combination (shown in boldface) represents the "baseline," that is, based on the scheduling algorithm considering only economic costs. The rows immediately below each baseline case are results based on the new algorithm including environmental impact (Equation 28). 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 5, together with the vehicle utilization results from Table 7, the three loading levels simulated represent cases of surplus capacity, adequate capacity, and capacity shortage. 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. This represents the elimination of "slack", which is further evidenced by the trend of increasing mean pick-up delay and decreasing on-time performance. We interpret the constancy of ridesharing as indicating it is primarily governed by the service and operational policies and constraints, together with the spatial and temporal distribution of requests.

The effects of the new algorithm in terms of cost and environmental performance may be seen in Table 6, as well as in Tables 8 and 9 comparing life-cycle environmental impacts. (From the regulatory perspective, in particular for Southern California, the criteria and other pollutant air emissions [Tables 8a and 9] 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 6, it should be seen immediately 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 5, 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." 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, as it is closest to the actual system on which our model is based.) Improvement occurs at all three levels of system loading. For example, in the 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. Further, all Case I improvements are statistically significant at the 95 percent (α=0.05) confidence level. 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 are also seen to result in Case II (heterogeneous fleet comprised of two vehicle types) at all system loading levels. All improvements are statistically significant at the 95% confidence level. For the homogeneous fleet case (Case III), while Table 8 indicates slight environmental 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 7, where the most obvious effect is the shifting of vehicle selection, i.e., from "dirtier" to "cleaner" vehicles. This is seen to occur (in the heterogeneous fleet cases) at all system loading levels.

Additionally, it should be seen that the 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 5. Finally, the number of engine starts and controllable (waiting) engine idling also appear to decrease slightly with increasing environmental objective weight.

Tables 5 – 9 here

7. CONCLUSION

In this paper, we developed a methodology for the combined routing and scheduling of fleet vehicles, where environmental impacts were assessed using environmental life-cycle impact assessment methods, and these impacts were included in the scheduling algorithm and optimization objective function. We demonstrated the methodology for a demand-responsive 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. 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. In particular, we would expect this to be true so long as distance- and penalty-related costs and environmental impacts are uncorrelated. 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. Finally, it should be seen that when the objective function includes both cost and environmental impact objectives, the “best” fleet composition is not, necessarily, a fleet comprised exclusively of vehicles selected to optimize one objective or the other.

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