Title

Tradeoffs between Costs and Greenhouse Gas Emissions in the Design of Urban Transit Systems

Author
Griswold, Julia Baird

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Tradeoffs between Costs and Greenhouse Gas Emissions
in the Design of Urban Transit Systems

by

Julia Baird Griswold

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Committee in charge:

Professor Samer Madanat, Co-Chair
Professor Arpad Horvath, Co-Chair
Professor Robert Cervero
Professor Carlos Daganzo

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Abstract

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Public transit is often touted as a “green” transportation option and a way for users to reduce their environmental footprint by avoiding automobile emissions. Many transit systems, however, have considerable emissions, and when vehicles run with ridership significantly below capacity, the per-passenger-kilometer emissions can be greater than for automobile. Efforts to reduce public transit emissions have centered on shifting users from more polluting modes and improving technology either by retrofitting existing vehicles or replacing them with more efficient models. I explore an approach to optimizing the design and operations of transit systems for both costs and emissions using continuum approximation models. The research identifies the Pareto frontier for designing an idealized transit network, and compares transit modes, including bus, bus rapid transit, light rail, and metro heavy rail, over four city scenarios. The slope at any point on the Pareto curve represents the cost of decreasing emissions by another unit, and this can be used to identify an emissions level that is equal to the market value of carbon. Further, I explore how the level of service for users impacts emissions: first, comparing modes at a given emissions level to see which provides the best service to users in terms of average travel time; second, incorporating travel time elasticities into the optimization to allow demand to reduce subject to increases in the travel time. Results of the parametric analysis suggest that a BRT system is a low cost and low emissions transit option for many types of cities. Choosing GHG reduction levels based on the market price of carbon has a small impact on user travel time, so further reductions may be reasonable. In general, the lowest-cost mode will provide the fastest travel time to users at a given emissions level. When shifting demand is accounted for, emissions reductions are moderated, but not eliminated, by the increase in automobile emissions when users are relatively inelastic. Including automobile emissions in the optimization shifts the

problem from the agency to the city perspective and produces results that can avoid the unintended emissions consequences associated with users changing modes. This research provides a strategic framework for transit agencies to cost-effectively reduce GHG emissions, demonstrating how operational and network changes can be used to reduce the costs and emissions of a transit system. The methods can be used to estimate the system cost of GHG emissions reductions to facilitate comparison with other approaches, such as vehicle replacement or engine upgrades. One can identify the scale of reasonable reductions and estimate the net effect on emissions as service is reduced and users switch modes.

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Chapter 1. Introduction

Public transit is often touted as a “green” transportation option and a way for users to reduce their environmental footprint by avoiding automobile emissions. Many transit systems, however, have considerable emissions, and when vehicles run with ridership significantly below capacity, the per-passenger-kilometer emissions can be greater than for automobile (Chester and Horvath 2009). Recent investments in this sector to address greenhouse gas (GHG) emissions have concentrated on purchasing efficient replacement vehicles and inducing mode shift from the private automobile (Gallivan and Grant 2010). However, there has been little focus on the potential of operational improvements to reduce transit emissions. It is known that increasing stop spacing can reduce bus emissions (Saka 2003), but there are many other operational and network design improvements that have not been considered. Examining a city transit network, there is the potential to reduce both costs and emissions by improving system efficiency.

The objective of this research is to evaluate the potential benefit of design and operational approaches to improving the environmental efficiency of transit systems. This dissertation examines the extent to which system characteristics (i.e., headway, route spacing, and stop spacing) and trunk technology (i.e., heavy rail, light rail, and bus) can be modified to reduce GHG emissions and user and agency costs. The research employs continuum approximation models to design a grid transit network for GHG emissions and social cost minimization, identifying the Pareto frontier for designing an idealized transit network. Along the Pareto frontier there is a tradeoff between system costs and GHG emissions. GHG emissions are reduced by small reductions in level of service to users, who must suffer increases in travel time. In the first portion of analysis, demand is considered exogenous, but in a subsequent phase, I also examine how the demand is affected by changes in service. It is assumed that some users will shift to more polluting modes when their travel time increases, thus causing automobile emissions that offset some or all of the transit emissions reductions. This research focuses on the network design and operation of transit systems with a uniform many-to-many demand pattern. A grid network is considered for simplicity. Decision variables include headway, stop spacing, and route spacing. Four different trunk line technologies are considered: metro (heavy) rail, light rail transit (LRT), bus rapid transit (BRT), and bus. The environmental metric is life-cycle GHG emissions. The scope of the life-cycle emissions and costs includes infrastructure construction, system maintenance, and vehicle manufacturing and operations. Although a metric of energy would help avoid an assumption of electricity mix, GHG emissions provide a more direct measure of the environmental impact. Other environmental emissions, particularly criteria air pollutants, are outside the scope of this research.

This research provides a strategic framework for transit agencies to cost-effectively reduce GHG emissions, demonstrating how operational and network changes can be used to reduce the costs and emissions of a transit system. The methods can be used to estimate the system cost of GHG emissions reductions to facilitate comparison with other approaches, such as vehicle replacement or engine upgrades. One can identify the scale of reasonable reductions and estimate the net effect on emissions as service is reduced and users switch modes. One can also estimate the possible emissions consequences of reducing transit service, as user shift to other modes. These approaches can be applied in the design of new transit systems or in modifying existing bus networks.

The dissertation is structured in the following way. Chapter 2 describes the existing literature in the areas of quantifying emissions from public transit, the efforts to reduce or optimize transit emissions, and the methods used to optimize transit for costs. Chapter 3 presents the simplifying assumptions made about the structure of a grid-network city and the continuum approximation models used to optimize the transit network design for costs and emissions. In Chapter 4, I compare the optimal designs for each mode for four different city scenarios and look at two approaches to reducing GHG emissions below the cost-optimal level. First, I examine the user travel time impact of choosing the emissions level based on the societally optimal cost of emissions reduction, or the market carbon price. Next, I compare the modes at a given emissions level. In Chapter 5, I incorporate user travel time elasticities to adjust user demand based on the increase in travel time as service is reduced, first from the agency perspective and then from the city perspective, by including the marginal automobile emissions in the constraint. Chapter 6 presents sensitivity analysis on the emissions parameters and discussion of my confidence in the travel time estimate and parameters for emissions and costs. Chapter 7 concludes with a review of significant findings, discussion of some study limitations, and recommendations for future work.

Chapter 2. Literature Review

The literature review begins with a discussion of public transportation emissions inventories, approaches to reducing emissions, and how those emissions are affected by transit operations. The second part describes models for optimizing transit operations.

2. 1 Emissions from Public Transportation

Many studies have attempted to quantify or compare the emissions from buses (Herndon et al. 2005; Puchalsky 2005; Ally and Pryor 2007; Chester and Horvath 2009; Cui et al. 2010) and rail transit (Puchalsky 2005; Messa 2006; Chester and Horvath 2009), but fewer have attempted to examine the life cycle beyond the operations phase (Ally and Pryor 2007; Chester and Horvath 2009; Chester et al. 2010; Cui et al. 2010). This discrepancy may be due to a greater policy focus on tailpipe emissions. As well, estimating the environmental effects of infrastructure is complicated. While Puchalsky (2005) compared emissions from bus rapid transit (BRT) and light rail transit (LRT), he only examined emissions from the operation of the vehicles, omitting the significant emissions for infrastructure construction, maintenance, and operation identified by Chester and Horvath (2009). Furthermore, life-cycle assessment studies have generally been case studies, making it difficult to generalize results to other locations and various technologies. For example, emissions from electric rail services are dependent on the local electricity mix (Messa 2006; Chester and Horvath 2009). Emission factors can also be used to estimate emission inventories of the operational phase for diesel buses or rail engines in mobile emission models (Jamriska et al. 2004; Morawska et al. 2005).

A recent Transit Cooperative Research Program report (Gallivan and Grant 2010) identifies several ways in which transit agencies are reducing GHG emissions: expanding transit service, increasing vehicle passenger loads, reducing roadway congestion, promoting compact development, alternative fuels and vehicle types, vehicle operations (e.g. anti-idling policies) and maintenance, construction and maintenance of infrastructure and facilities, and reducing emissions from facilities and nonrevenue vehicles. Some of these approaches, however, are not necessarily cost effective or effective at reducing emissions. The approaches can be generalized into those that reduce the emissions of the transit system (Cook and Straten 2001; Schimek 2001; Stasko and Gao 2010) and those that cause transit to displace other emission sources (Vincent and Jerram 2006; Hensher 2008; McDonnell et al. 2008). Schimek (2001) found that it is more economical to retrofit diesel engines rather than buy new vehicles, while Stasko and Gao (2010) developed a model for optimizing vehicle retrofit, replacement, and assignment decisions. Reductions due to displaced emissions are difficult to estimate or forecast as they require an understanding of how mode choice may be affected by improvements in transit service. A case study of several regions in Europe found that improved transit quality attracted non-motorized users, not drivers, causing a net increase in emissions (Poudenx 2008). As emissions per passenger-kilometer traveled are highly dependent on ridership (Chester and Horvath 2009), transit is not always less polluting than private automobiles.

While Gallivan and Grant (2010) mention "transit agency operations" in their report, their focus in that area is on the reduction of tailpipe emissions through engine upgrades and low-carbon fuels, reduction of energy consumption in facilities, and the impacts of construction and maintenance. Other operational improvements that could improve emissions include 1) increasing spacing between stops in order to increase the average vehicle speed and reduce the number of accelerations and decelerations, 2) signal priority, 3) using smaller vehicles, and 4) reducing the number of vehicles required to satisfy user demand. These approaches have not been discussed at length in the literature. In one study, an optimal bus stop spacing of 700 to 800 meters, rather than the U.S. average of 330 meters, was found to reduce fuel consumption and carbon dioxide emissions substantially by reducing stops and starts and increasing the average speed, but had little effect on other air emissions (Saka 2003). Others have examined ways of optimizing the assignment and scheduling of vehicles within a fleet to reduce total emissions (Beltran et al. 2009; Li and Head 2009; Gouge et al. 2013). Dessouky et al. (2003) jointly optimized costs, service, and emissions for a demand-responsive minivan and shuttle bus transit service, but a similar approach has not yet been applied to fixed-route public transportation systems and the results of their simulation for Los Angeles County are not generalizable to other cities. Diana et al. (2007) compared the emissions impacts of traditional fixed-route and demand- responsive service at different demand and services levels. Emissions were based solely on distance traveled, and analysis ignored the potential impacts of average speed, acceleration, and deceleration.

2.2 Public Transportation Network Design

There have been numerous studies on transit system design, but very few have included any environmental metrics (Dessouky et al. 2003; Saka 2003; Diana et al. 2007, described above). Continuum approximation (CA) models have been used to optimize transportation network design to minimize system and user costs. These models can provide general insights into how to structure efficient transit systems by making generalizations that simplify the analysis. Several studies have used CA to optimize stop spacing (Wirasinghe and Ghoneim 1981; Kuah and Perl 1988; Parajuli and Wirasinghe 2001) along with other network attributes such as headway (Chien et al. 2010). Others have examined the structure of transit networks, such as grids, radial systems (Byrne 1975; Tirachini et al. 2010), and hub-and-spoke systems (Newell 1979). Tirachini et al. (2010) compared light rail, heavy rail, and BRT on a radial transit network.

Daganzo (2010) went a step further by determining a system design and operating characteristics that could make transit competitive with the automobile. Applying his models to Barcelona, he found that optimal service would reduce the total number of vehicles significantly, thus reducing total transit emissions. Sivakumaran et al. (2012) explored the influence of access mode on choice of trunk technology, and the research in this dissertation builds on the models developed for that research. Continuum approximation models are a promising approach for the joint optimization of costs and emissions, having been used for cost minimization in previous research.

Chapter 3. Methodology

Consider a large rectangular urban area with a dense grid road network (See Figure 3.1). The transit network consists of two sets of many parallel lines with uniform spacing, r_L and r_W, travelling lengthwise and widthwise to form a grid covering the city. Stops are equidistant with spacing s, and route spacing is an integer multiple of stop spacing ($r_L = p_L s$, $r_W = p_W s$). Headways between vehicles on each line are H. The density of trip origins is assumed to be uniform throughout the urban area, with travelers exhibiting a many-to-many demand pattern. Each user travels on foot along the grid street network to the nearest transit stop. The city can be described through several model parameters, which are listed in Table 3.1. The transit modes include diesel bus, BRT, LRT, and metro heavy-rail transit. Cost and emissions parameters for each mode are given in Table 3.2. The right-of-way (ROW) infrastructure parameters (C_I, E_I) include the maintenance of pavement for bus and BRT, the construction of the track for LRT and metro, and the construction of a combination of underground, at-grade, and aerial right-of-way for metro. The station parameters (C_S, E_S) account for the construction of the stations, and the vehicle parameters (C_V, E_V) account for the acquisition, operation, and maintenance of transit vehicles. For inclusion in the model, these parameters have been prorated over the planning horizon into the hourly units required by the model. Their derivation is described in detail in the appendices. The infrastructure for the BRT system is based on the proposed design for the Geary Blvd BRT, LRT is based on the Muni Metro system, and metro is based on the Bay Area Rapid Transit (BART) system, all in the San Francisco Bay Area in California. Emissions estimates were taken from Chester and Horvath (2009).

Table 3.1. Model parameters for city

Parameter	Description	Value	Units
δ	Demand density	Varies	pax/km^2-hr
L	Length of urban area	Varies	km
W	Width of urban area	Varies	km
v_a	User access speed	5	km/hr
μ	User value of time	Varies	\$/hr

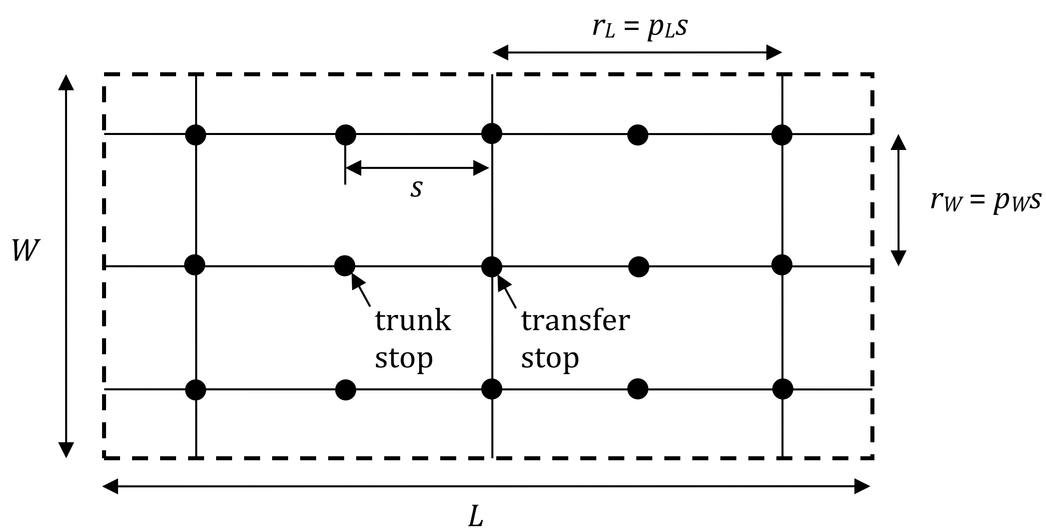

Figure 3.1. Rectangular city (L x W) with a grid-trunk system

Table 3.2. Mode-specific model parameters

Param	Description	Units	Bus	BRT	LRT	Metro
v	Commercial speed	km/hr	25	40	40	60
τ	Lost time/stop	sec.	30	30	30	45
T	Lost time/transfer	sec.	20	30	30	60
C_I	ROW infrastructure cost	\$/km-hr	10	36	220	260
C_V	Vehicle purchase, fuel & maintenance cost	\$/veh-km	1.0	1.6	6.0	8.9
C_M	Labor cost	\$/veh-hr	150	200	200	250
C_S	Station construction cost	\$/st-hr	0.82	8.2	11	130
E_I	ROW infrastructure emissions	g/km-hr	8.1	160	790	44,000
E_V	Vehicle fleet manufacturing, operation & maintenance emissions	g/veh-km	1,700	2,200	2,700	11,000
E_S	Station construction emissions	g/st-hr	170	1,700	1,700	120,000

Developing analytical expressions for user cost and system emissions allows for the evaluation of trade-offs between level of service for users and environmental impacts with different values of the decision variables (see Table 3.3). Optimal values of H, p, and s can be chosen to minimize total system cost subject to a GHG emissions constraint, which can then be varied. The total system cost is the sum of the user and agency costs, and the cost expressions were taken from Sivakumaran et al. (2012). User cost (Z_{user}) is made up of the sum of the:

- expected access and egress time, $(0.5r_L + 0.5r_W + s)\frac{1}{2v_a}$,
- wait time, $\frac{H}{2}$,
- transfer time, $\frac{H}{2} + T$,
- and vehicle travel time, $(L + W)\left(\frac{1}{3v} + \frac{\tau}{3s}\right)$

multiplied by the total demand, $D = \delta L^2$, and wage rate, μ. Wage rate serves as a proxy for value-of-time. Agency cost (Z_{agency}) is driven by:

- the total infrastructure length of the system, $\mathrm{LW}\left(\frac{1}{\mathrm{r_W}} + \frac{1}{\mathrm{r_L}}\right) = \frac{\mathrm{LW}}{\mathrm{s}}\left(\frac{1}{\mathrm{p_W}} + \frac{1}{\mathrm{p_L}}\right)$,
- the number of stations in the system, $\frac{\mathrm{LW}}{\mathrm{s}^2}\left(\frac{1}{\mathrm{p_W}} + \frac{1}{\mathrm{p_L}}\right)$,
- the total vehicular distance travelled by transit vehicles in an hour of operation, $\frac{2\mathrm{LW}}{\mathrm{sH}}\left(\frac{1}{\mathrm{p_W}} + \frac{1}{\mathrm{p_L}}\right)$,
- and the vehicle fleet size, $\frac{2\mathrm{LW}}{\mathrm{sH}}\left(\frac{1}{\mathrm{p_W}} + \frac{1}{\mathrm{p_L}}\right)\left(\frac{1}{\mathrm{v}} + \frac{\tau}{\mathrm{s}}\right)$.

Using these expressions, the system cost function (Z_{system}) is given by:

$$Z_{system}\ (\$/\mathrm{yr}) = \left((0.5r_L + 0.5r_W + s)\frac{1}{2v_a} + H + T + (L+W)\left(\frac{1}{3v} + \frac{\tau}{3s}\right)\right)\mu D$$

$$+\frac{LW}{s}\left(\frac{1}{p_W} + \frac{1}{p_L}\right)C_I + \frac{2LW}{sH}\left(\frac{1}{p_W} + \frac{1}{p_L}\right)C_V + \frac{2LW}{sH}\left(\frac{1}{p_W} + \frac{1}{p_L}\right)\left(\frac{1}{v} + \frac{\tau}{s}\right)C_M + \frac{LW}{s^2}\left(\frac{1}{p_W} + \frac{1}{p_L}\right)C_S \quad (3.1)$$

Table 3.3. Decision variables

Decision Variable	Description	Units
H	Transit vehicle headway	hr
p	Route spacing factor	km
s	Stop spacing	km

GHG emissions are measured in carbon dioxide equivalents, a metric that normalizes all GHG emissions to the equivalent mass of CO_2. The total operating GHG emissions per year, $Z_{emissions}$, is based on the system emissions because there are negligible emissions for the user when the access mode is walking. The formulation is identical to the agency cost expression, except that the term corresponding to labor cost is removed because there are no emissions assigned to labor:

$$Z_{emissions}\ (\mathrm{g\ CO_2e/yr}) = \frac{LW}{s}\left(\frac{1}{p_W} + \frac{1}{p_L}\right)E_I + \frac{2LW}{sH}\left(\frac{1}{p_W} + \frac{1}{p_L}\right)E_V$$

$$+\frac{LW}{s^2}\left(\frac{1}{p_W} + \frac{1}{p_L}\right)E_S \quad (3.2)$$

This constrained optimization involves conflicting objectives which can be displayed using Pareto curves. Using the above models and the associated parameters, one can solve for the values of the decision variables that minimize the total system cost subject to an emissions constraint:

$$\mathrm{Min}\ Z_{system} = Z_{user} + Z_{agency} \quad (3.3)$$

$$s.t.\ \ Z_{emissions} \le E$$

where E is a GHG emissions constraint. By varying E, one can develop a set of optimal system characteristics, H^*, p^*, s^*, for given emissions goals. These Pareto curves are bound at one end by the system cost-optimal point where increases to E will provide no additional cost reductions. The other end of the curve is unbounded.

Once an optimal system is obtained, one can observe the behavior of the cost and emission models. For example, Figure 3.2 shows hypothetical optimal system, user, and agency cost curves for a transit system as the GHG emission constraint varies. The vertical bar at the right of the curve marks the system cost-optimal point, where further increases in emissions will not reduce the costs. Agency costs increase with emissions while user costs decrease with emissions. The agency costs decrease when emissions are constrained because emissions reductions are caused by reductions in service. Excessive reductions in service levels may cause riders to abandon public transit for personal vehicles. User costs can rise significantly when emission reductions are steep, as shown at the extreme left of the graph in Figure 3.2.

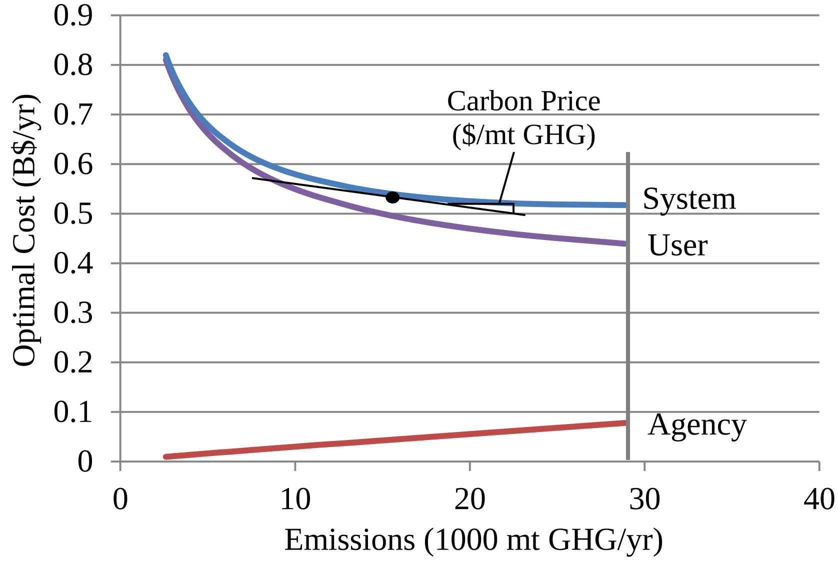

Figure 3.2. Hypothetical system, user, and agency costs by GHG emissions level

The Pareto curves of optimal system cost and emissions can be used in several ways to inform transit system design. The slope of a tangent on the Pareto curve is the shadow price at the tangent point, or the cost of reducing emissions by an additional unit. This curve can be used to determine how much to reduce emissions by finding the point at which the shadow price is equal to the market carbon price. That point indicates the economically efficient combination of cost and GHG emissions (See Figure 3.2). Beyond that point, the cost of reducing an additional unit of emissions would be greater than the price of carbon on the market. An example of the carbon price analysis is described in Chapter 5.

Chapter 4. Parametric Analysis

The optimal system design depends largely on the type of city for which the system is being designed. The following section presents the results of parametric analysis of the three model parameters that describe city characteristics, city size (L, W), demand density (δ), and wage rate (μ). Since demand density and wage rate appear as a product in a single term (μ δ) in the cost expression, it is meaningless to vary them individually. Hereon, I will refer to the product of μ and δ as β. I consider small (L=W=10 km) and large (L=W=40 km) city sizes, low passenger demand densities (δ=100 pax/km^2/hr) and wage rates (μ=\$10/hr) (β=\$1000 pax/km^2/hr^2), and high passenger demand densities (δ=200 pax/km^2/hr) and wages (μ=\$20/hr) (β=\$4000 pax/km^2/hr^2). The parameter values were chosen for hypothetical cities and do not necessarily reflect standard definitions of low and high values for the city characteristics. They combine into four possible city scenarios, described in Table 3.4.

Table 3.4. City scenarios

	City Size (L,W) (km)		Demand Density (δ) (pax/km^2/hr)		Wage Rate (μ) ($/hr)		$\beta = \mu\delta$ ($-pax/km^2/hr^2)	
Scenario 1	Small	10	Low	100	Low	10	Low	1000
Scenario 2	Small	10	High	200	High	20	High	4000
Scenario 3	Large	40	Low	100	Low	10	Low	1000
Scenario 4	Large	40	High	200	High	20	High	4000

The hypothetical cities in the parametric analysis do not represent actual cities, but the relative characteristics do resemble some real U.S. cities. For example, scenario 1 is similar to Fresno, California, scenario 2 to San Francisco, scenario 3 to Kansas City, Missouri, and scenario 4 to New York City or Chicago.

Beginning with pair-wise analysis of the four city scenarios, you can observe the system changes that occur when β is changed. Figure 4.1 shows the Pareto frontiers for optimal transit system design by mode for a small city with low (Scenario 1) and high values of β (Scenario 2). For scenario 1, BRT maybe the lowest cost option for most values of the GHG emissions constraint. At the cost-optimal point at the right end of the curve, however, bus and LRT have lower emissions than BRT. Metro is not competitive in this scenario as its costs are higher than both bus and BRT and its emissions at the cost-optimal point are about four times that of the other modes. The attributes of the systems at the cost-optimal point (shown in Table 4.1) reveal how the mode parameters impact the relative costs and emissions. The low infrastructure cost of bus allows for small stop (*s*=0.8 km) and route (*ps*=1.6 km) spacing compared to the other modes, which have route spacing between 1.8 and 3.6 km. The small spacings for bus make access on foot easier, and thus keep the out-of-vehicle travel time much lower (14 minutes, or 58% lower than metro). BRT, which is faster than bus, has a slight edge in system cost because the travel time is 5 minutes shorter. LRT is able to be competitive for emissions because it has cost-optimal route spacing 50 percent higher than bus or BRT, so the length of ROW infrastructure, number of stations, and number of vehicles in operation are lower. The emissions results in Tables 4.1 and 4.2 shown to no more than two significant digits because the quality of the data and the accuracy of the model do not justify greater precision. The chapter on sensitivity analysis provides further explanation.

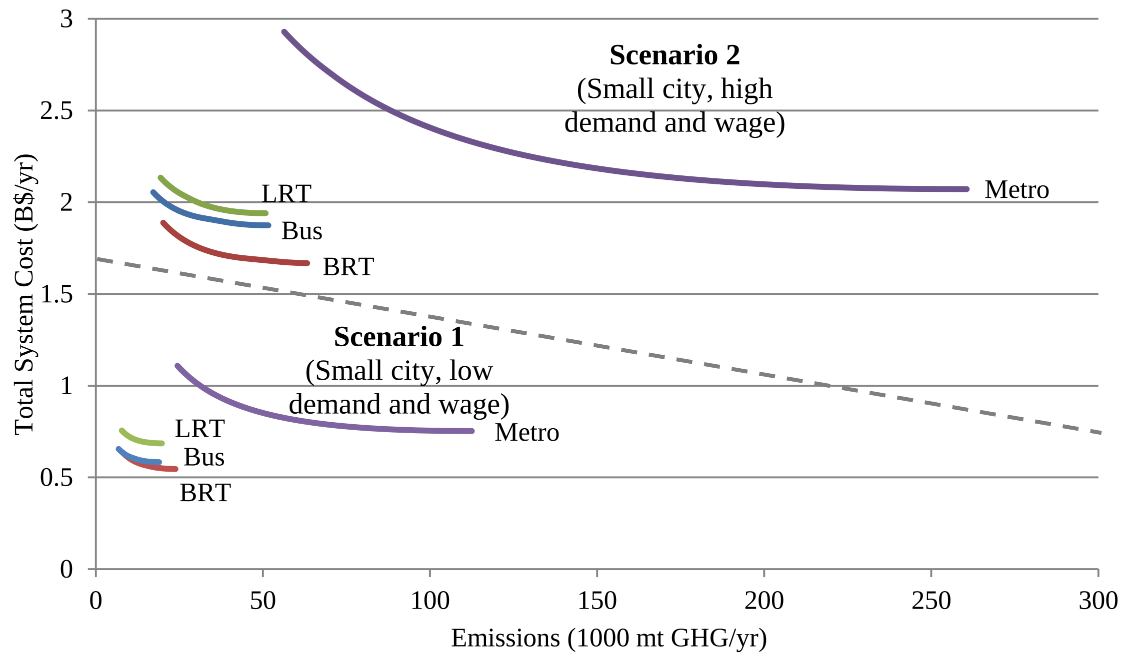

Figure 4.1. Pareto frontiers of optimal transit system design for a small city (L=W=10 km) for bus, BRT, LRT, and metro

Table 4.1. Cost-optimal decision variables, costs, emissions, and average travel time (TT) for a small city

	p	*s* (km)	*H* (min)	Zsystem ($B)	GHG (1000 mt)	TT (min)	OVTT (min)
Scenario 1	(Small city, low demand and wage)						
Bus	2	0.8	9	0.6	19	44	24
BRT	2	0.9	8	0.5	25	39	25
LRT	3	1.0	8	0.7	20	45	31
Metro	3	1.2	8	0.8	110	49	38
Scenario 2	(Small city, high demand and wage)						
Bus	1	0.9	6	1.9	52	37	17
BRT	1	1.0	6	1.7	67	31	18
LRT	2	0.8	5	1.9	51	35	21
Metro	2	1.0	5	2.1	260	36	25

When β is quadrupled (Figure 4.1 – Scenario 2), the costs and emissions increase for all modes. With the increase in value of time for users, the agency must improve service to minimize the system cost. The cost-optimal route spacings for bus and BRT are cut nearly in half and the route spacings for the other modes are also reduced. Along with the decrease in headways, the service improvements lead to a reduction in travel time for users at the cost-optimal point. While bus and LRT have lower cost-optimal emissions, BRT service has a lower cost and a greater travel time advantage than in the low β scenario.

Comparison of the remaining scenarios (Figure 4.2) reveals similar patterns between low and corresponding high β cities. Additionally, one can observe that, with an increase in β, bus systems have significant loss in cost advantage relative to the other modes. In the large cities the benefit of short access distances for bus is outweighed by the disbenefit of the slow speed and many stops that increase the travel time. Improved service is required to balance the increased impact of user costs as the number of users and their wages increase, and this service increases both the agency costs and emissions. As shown in Table 4.2, the service improvements help to reduce the travel time for users compared to the low β cities (Scenarios 1 and 3) by reducing headways and route spacing. Bus has the greatest headway reductions, the smallest route spacing reductions, and the smallest travel time reductions. The route and stop spacings appear to be as low as they can optimally be because of the tradeoff between access time and stop time in the vehicle. For metro travel time is reduced up to 20 percent as route spacing and headway reductions reduce out-of-vehicle time without increasing in-vehicle travel time. Headway is not a factor in in-vehicle travel time because it only relates to wait time, and route spacing has a minor impact for these changes because of the speed of the vehicles over the short distances. Stop spacing would have a greater impact on in-vehicle travel time because it affects how times the transit vehicle must stop on a trip, but the value of stop spacing remains consistent between the scenarios. Scenario 4, which most resembles a high-density metropolis, is the only case where metro has the lowest travel time, but BRT still has a slight cost advantage that, however, may not be significant. It is expected that the addition of bus feeder service will provide additional advantages to BRT, LRT and metro for larger, higher-density cities. With faster access to stations, the fast trunk modes can operate with larger stops spacings, thus reducing user in-vehicle travel time and agency costs (Sivakumaran et al. 2012).

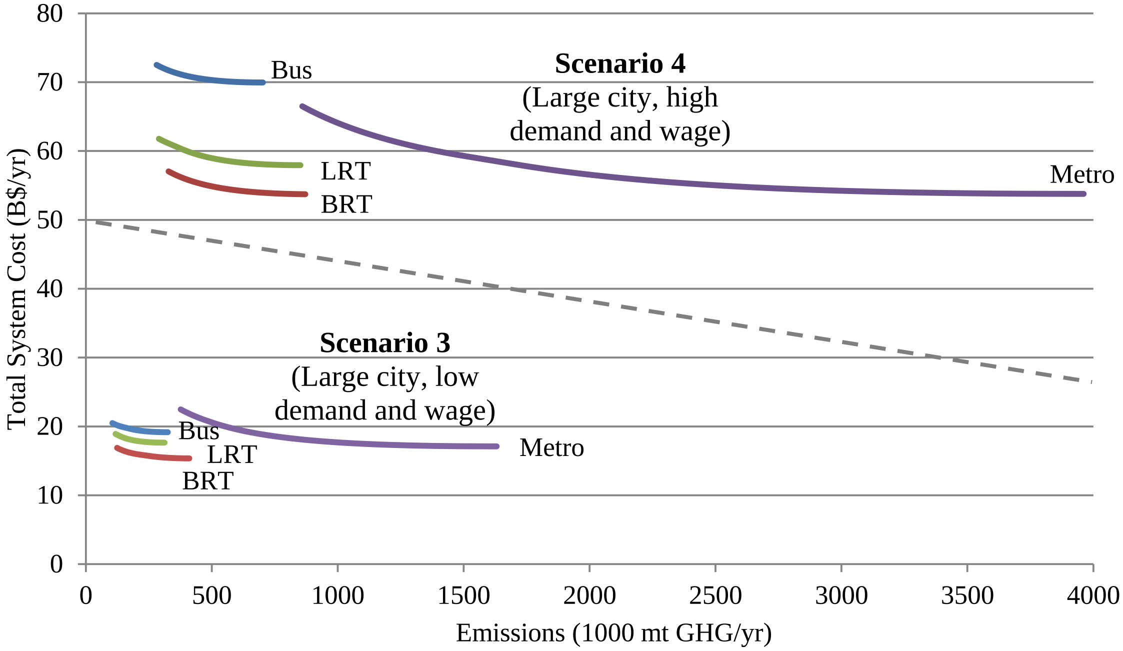

Figure 4.2. Pareto frontiers of optimal transit system design for a large city (L=W=40 km) for bus, BRT, LRT, and metro

Table 4.2. Cost-optimal decision variables, costs, emissions, and average travel time (TT) for a large city

	p	*s* (km)	*H* (min)	Zsystem ($B)	GHG (1000 mt)	TT (min)	OVTT (min)
Scenario 3	(Large city, low demand and wage)						
Bus	1	1.6	8	19	330	100	28
BRT	1	1.7	8	15	420	77	29
LRT	2	1.5	8	18	310	84	35
Metro	2	1.8	8	17	1600	79	41
Scenario 4	(Large city, high demand and wage)						
Bus	1	1.3	5	70	700	95	21
BRT	1	1.4	5	54	920	71	21
LRT	1	1.6	5	58	850	73	25
Metro	1	1.9	5	54	4000	66	29

Increasing the city size brings about a different set of system changes. The average travel distance is increased, thus the in-vehicle travel time takes up a greater proportion of the trip. The costs and emissions increase by an order of magnitude because of the larger coverage area for service. Between scenarios 1 and 3, the cost-optimal route spacing and headways are relatively consistent, but the stop spacing nearly doubles (Figure 4.2). This change increases the access time on foot, but also reduces the in-vehicle travel time by reducing the number of stops the vehicle makes. BRT is the optimal system for costs and is competitive for emissions in both large city scenarios (scenarios 3 and 4). The large cities require greater infrastructure mileage to serve the area, as well as higher speeds to reduce the travel times. BRT has the benefit of lower infrastructure costs than LRT and metro, which allows for greater coverage at a low cost and higher speed than bus, which makes up for the slightly longer access time. Regardless, many of the emissions results are significantly different (>±10%) when compared using one significant digit.

The results of the parametric analysis suggest that a BRT system could be the best low-emissions option for many types of cities, and is also the lowest cost option. Bus is a low cost option in small cities, but BRT is lower cost when the wage rate and demand density are high. The optimal system attributes (*p*, *s*, *H*) vary between city types, so it is important that the analysis be repeated with the parameters of a specific city before a new system is designed. Metro, although cost competitive in the large cities, has emissions on the order of four times greater than any of the other modes for all scenarios. The emissions parameters used for metro, which were based on the BART system in the San Francisco Bay Area, were about an order of magnitude higher than any of the other modes. Modeling after a different metro system could potentially produce more favorable emissions results.

4.2 Carbon Price Analysis

Another way to present the optimization results is to show the change in travel time and GHG emissions as the carbon price is increased relative to the cost-optimal point on the Pareto frontier, where an optimal agency would operate. This carbon price analysis of optimal transit systems allows for determination of the economically efficient level of GHG reduction. By operating at the point on the curve where the shadow price is equal to the carbon price, the system can avoid investing more than the market value in achieving additional GHG reductions. As an example here, I look at scenario 2 and scenario 3 and examine the changes that occur as the price of carbon is increased. In Figures 4.3 and 4.4, the dashed lines show the percentage change in GHG emissions as the carbon price increases, and the solid lines show the percentage change in travel time with increase in carbon price. For scenario 2, the travel time increases faster than for scenario 3, but the changes in emissions are similar. The vertical jog in the lines for BRT in Figure 4.3 shows the point where the optimal route spacing factor increases by one. With the large increase in route spacing, the emissions are reduced slightly more, but the travel time for users increases significantly. In general, the GHG emissions reduce more quickly than the travel time increases. Bus has the smallest reductions in emissions, while BRT has the smallest increase in the travel time for the range of carbon prices. Figures 4.3 and 4.4 show carbon prices up to $3,000, much higher than seen in the literature ($5-$65, IWGSCC 2010; $115, Knittel and Sandler 2011), but which corresponds to a travel time increase of less than 10 percent for LRT. For a carbon price of $100/mt, the potential emissions reductions are at most 6% and the corresponding travel time increase is negligible (less than a minute) because the cost increase is spread among many users in the system. Achieving these small reductions in emissions will cause almost imperceptible service changes to the system. This result suggests that greater GHG emissions reductions beyond a realistic market value of carbon could be implemented without inducing users to shift to other modes.

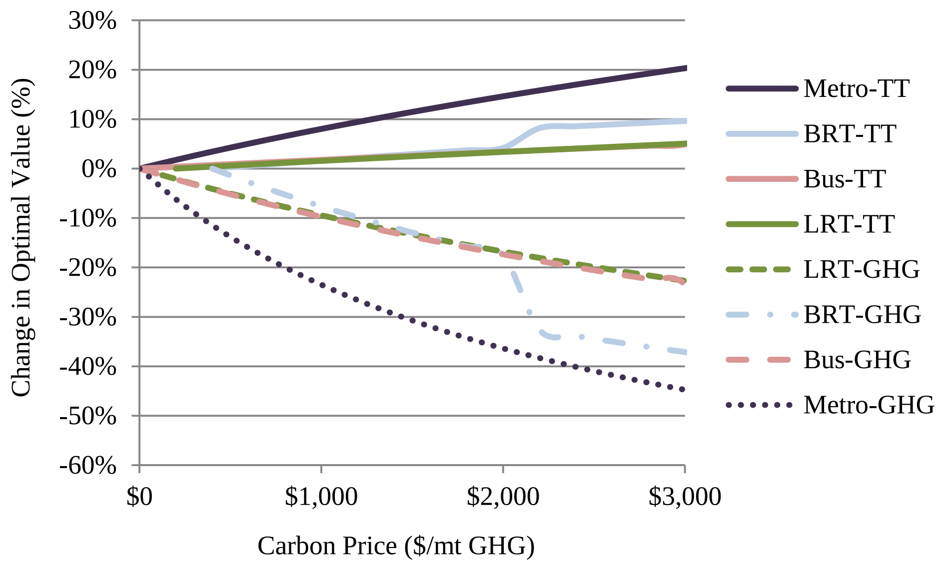

Figure 4.3. Change in GHG emissions and travel time with carbon price for scenario 2

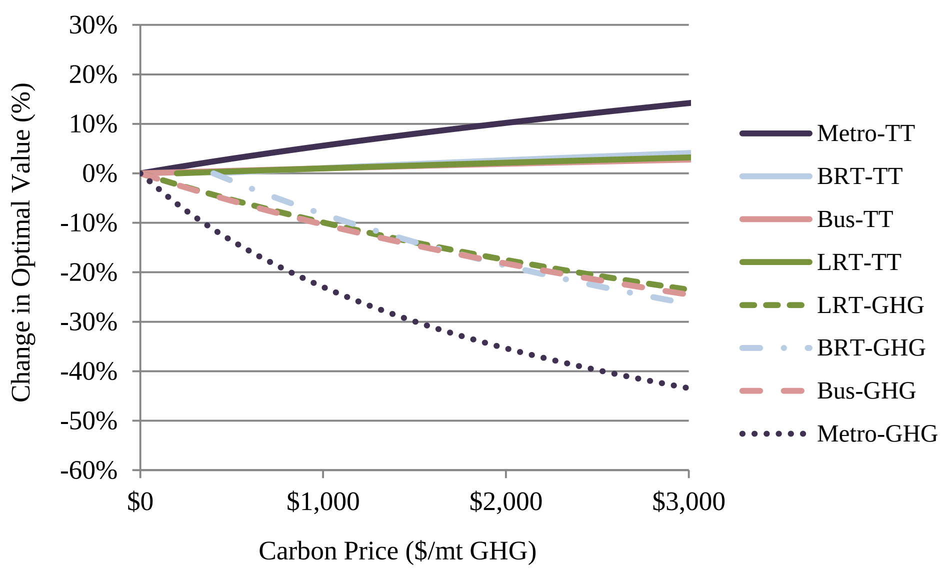

Figure 4.4. Change in GHG emissions and travel time with carbon price for scenario 3

4.3 Comparing modes by emissions level

The preceding section presented a comparison of modes at the cost-optimal point and observed the shape of the Pareto frontiers as the emissions constraint was reduced. For scenario 2, the city that was similar to San Francisco, California, BRT had the lowest system cost at any given emissions levels, but LRT had the lowest emissions at the cost-optimal point; it was unclear which mode provided the best service to users at a given emissions level. In this section, I set the emissions constraint to the cost-optimal emissions for LRT and compare the modes. The results are shown in Table 4.3, where you can see that the two lower cost modes, bus and BRT, also have the lowest average total travel time (TT) for users. For bus, the system changes are so small that the differences in the decision variable values do not show with two significant digits. Metro is not competitive for travel time; eighty-four percent of the 62-minute travel time for metro is in the out-of-vehicle travel time (OVTT), which shows the impracticality of having exclusively walking access to a metro system with infrequent stops. The headways for metro also nearly triple, making the wait and transfer times considerably longer. The emissions level for BRT is slightly higher (53,000 mt GHG/y) than the other modes because the constraint value falls in a range between two integer values for the route spacing factor.

Table 4.3 also shows the carbon price value, or the cost of decreasing emissions by a single unit, at the given emissions level. The value of bus ($150/mt GHG) is within an order of magnitude of carbon prices seen in the literature ($5-$65, IWGSCC 2010; $115, Knittel and Sandler 2011), but the values for BRT ($1,750/mt GHG) and metro ($21,050) are considerably higher than any realistic market value. Regardless, since BRT has the lowest cost and travel time at this emissions level, it would be the mode of choice for a system with this emissions goal.

Table 4.3. Optimal results by mode for the cost optimal point (Carbon Price = $0/mt) and when emissions are restricted for scenario 2

Mode	p	s (km)	H (min)	Zsystem (B$/y)	Emissions (1000 mt/y)	TT (min)	OVTT (min)	Carbon Price ($/mt)
Bus	1	0.9	6	1.9	52	37	17	0
	1	0.9	6	1.9	51	37	17	150
BRT	1	1.0	6	1.7	66	31	18	0
	1	1.0	7	1.7	53	33	19	1,750
LRT	2	0.8	5	1.9	51	35	21	0
	2	0.8	5	1.9	51	35	21	0
Metro	2	1.0	5	2.1	220	36	25	0
	3	1.5	14	2.8	51	62	52	21,050

For the city scenario that is similar to Kansas City, Missouri (L=W=40 km, β = 1,000, i.e., large city with low transit demand and low wage-earning transit users), the same analysis produces a similar outcome. Here, LRT is the lowest-emissions system at the cost-optimal point, but it is higher in cost than a bus. BRT is the lowest-cost system and it also has the lowest travel time for users when emissions are constrained to 310,000 mt GHG/y, the cost-optimal emissions for LRT (Table 4.4). Although the unconstrained optimal cost for metro is competitive with the other modes, its emissions are a factor of four greater, and the costs and travel time at the constrained emissions level are more than 50 percent greater. Again, metro loses competitiveness due to the high access time of walking and the long headways.

Table 4.4. Optimal results by mode for the cost optimal point (Carbon Price = $0/mt) and when emissions are restricted for scenario 3

Mode	p	s (km)	H (min)	Zsystem (B$/y)	Emissions (1000 mt/y)	TT (min)	OVTT (min)	Carbon Price ($/mt)
Bus	1	1.6	8	19	330	100	28	0
	1	1.6	9	19	310	100	28	350
BRT	1	1.7	8	15	420	77	29	0
	1	1.8	10	15	310	80	32	2,400
LRT	2	1.5	8	18	310	84	35	0
	2	1.5	8	18	310	84	35	0
Metro	2	1.8	8	17	1400	79	41	0
	3	2.8	23	23	310	124	90	25,500

Chapter 5. Effect of mode shift on GHG emissions

So far, the analysis has assumed that user demand is fixed and does not change subject to changes in the user travel time. In reality, it is expected that some users will shift to faster modes when the transit level of service is reduced. In this section, I examine how the emissions are affected by changes in demand due to reductions in service. By incorporating travel time elasticities into the model formulation, one can estimate the number of users who will switch to a faster mode, typically the automobile. Previous research has established a range of reasonable travel time elasticity values for transit in major U.S. cities. The elasticity values in Table 5.1 vary between estimates of 0.0 for bus walk time and −0.71 for transit access time, and −0.23 and −0.60 for in-vehicle travel time. These values are expected to be fairly robust because they are based on discrete choice models. The Kemp (1973) values are the least reliable as they are based on aggregate data, predating the development of discrete choice models. Although only the Small and Winston (1999) estimates match the location considered here, the values for the other U.S. cities suggest a reasonable range. Here, I examine the impact of total travel time elasticities between 0.0 and 1.0 to encapsulate all the reasonable values. Routes with higher frequency service tend to have smaller headway elasticities (Lago, Mayworm, and McEnroe 1981), possibly because small percentage changes to an already short travel time will mean smaller absolute changes than compared to infrequent service. For this reason, it is expected that the actual travel time elasticities for a city like San Francisco, a city with high frequency bus service, would be in the lower part of the range.

Table 5.1. Transit travel time elasticities from the literature

Description	Trip type	Value	Location	Mode	Source
In-vehicle time	Home based work tours	-0.39	Seattle area	Bus	Frank et al. (2008)
In-vehicle time	Work trips	-0.46	San Francisco East Bay	Bus	McFadden (1974)
In-vehicle time	Work trips	-0.39	Boston	Transit	Kemp (1973)
In-vehicle time	Home based non-work tours	-0.23	Seattle area	Bus	Frank et al. (2008)
In-vehicle time	Work trips	-0.60	San Francisco Bay Area	Bus, Rail	Small and Winston (1999)
Access time	Work trips	-0.71	Boston	Transit	Kemp (1973)
Walk time	Work trips	0.0	San Francisco East Bay	Bus	McFadden (1974)
Bus headway	Unspecified	-0.44 ±0.22	Detroit, Boston, Chesapeake/ Norfolk	Bus	Lago, Mayworm, and McEnroe (1981)
Rail headway	Unspecified	-0.50 ±0.20	Boston	Rail	Lago, Mayworm, and McEnroe (1981)
First wait time	Work trips	-0.17	San Francisco East Bay	Bus	McFadden (1974)
Transfer wait time	Work trips	-0.26	San Francisco East Bay	Bus	McFadden (1974)
Total travel time	Shopping trips	-0.59	Boston	Transit	Kemp (1973)

As an example of how emissions are affected by change in demand, one can represent the demand for transit as a Cobb-Douglas function ($Q = at^b$), where Q is the demand for transit, a is a constant, t is the travel time on transit, and b is the travel time elasticity. In the case of completely inelastic users ($b = 0$) (left side of Figure 5.1), the demand is constant ($Q = Q_0 = a$). When the travel time increases from t_0 to t_1, there is no change in demand. The shaded area labeled 1 represents the benefit to society of reduced GHG emissions from transit as the level of service is reduced. On the right side of Figure 5.1, $b = -1$, and demand for transit reduces from Q_0 to Q_1 when the travel time is increased from t_0 to t_1. Shaded area 2 represents the disbenefit to society as some users switch from transit to auto and their GHG emissions increase. Shaded area 3 represents the benefit to society as GHG emissions are reduced in the transit system that is now optimized for fewer users. This tradeoff determines whether there is an overall societal benefit of transit service reductions.

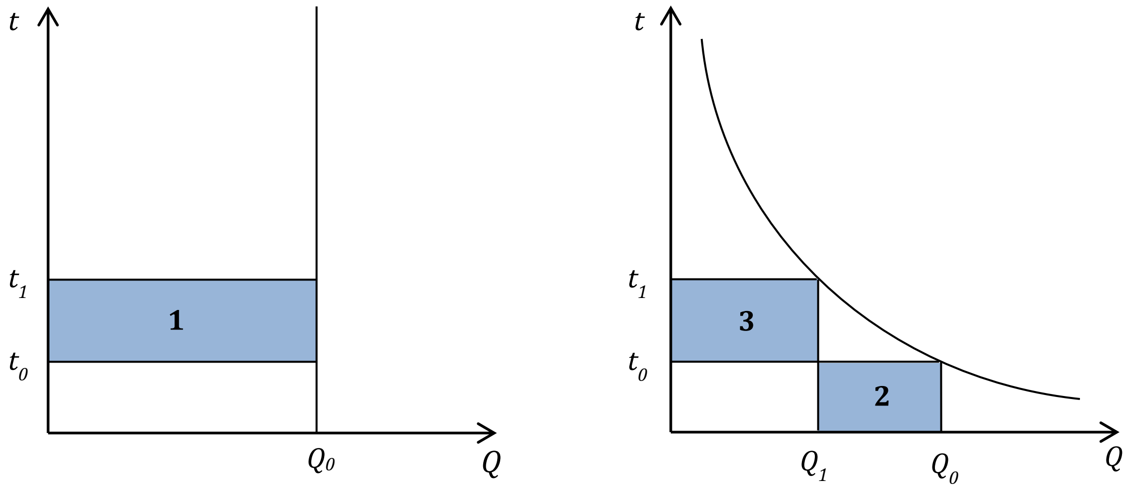

Figure 5.1. Cobb-Douglas demand functions for b = 0 (left) and b = -1 (right)

In the preceding analysis, Z_{user} is a function of the user demand for transit, which is fixed (elasticity = 0), and the average travel time for users. To incorporate variable demand into the model, it is necessary to account for the entire consumer surplus (Daganzo 2012), such that:

$$Z_{user,T} = -(consumer\ surplus) \times \mu \times L \times W \tag{5.1}$$

where T indicates that the costs are those related to transit. For the example of b = -1, the striped area in Figure 5.2 shows the consumer surplus for t_0 and the shaded area with stripes shows the reduced consumer surplus for t_1. To keep the units consistent, the demand function is modified to $Q = a\left(\frac{t}{t_o}\right)^b$, where t is the travel time, t_o is the cost-optimal travel time, and a is equal to the demand density (δ). The consumer surplus can be found by integrating the demand function between t and t_{max}, a very high number:

$$consumer\ surplus = \int_t^{t_{max}} a\left(\frac{t}{t_o}\right)^b dt = \begin{cases} at_o \ln t\big|_t^{t_{max}} & for\ b = -1 \\ \left.\dfrac{at_o\left(\frac{t}{t_o}\right)^{b+1}}{b+1}\right|_t^{t_{max}} & otherwise \end{cases} \tag{5.2}$$

The function is unbounded for the range of values for b (-1 through 0) considered here, so that the terms containing t_{max} can be simplified to a constant, which can be ignored for the purposes of the optimization.

$$consumer\ surplus = \begin{cases} -at_o \ln\left(\frac{t}{t_o}\right) + const & for\ b = -1 \\ -\dfrac{at_o\left(\frac{t}{t_o}\right)^{b+1}}{b+1} + const & otherwise \end{cases} \tag{5.3}$$

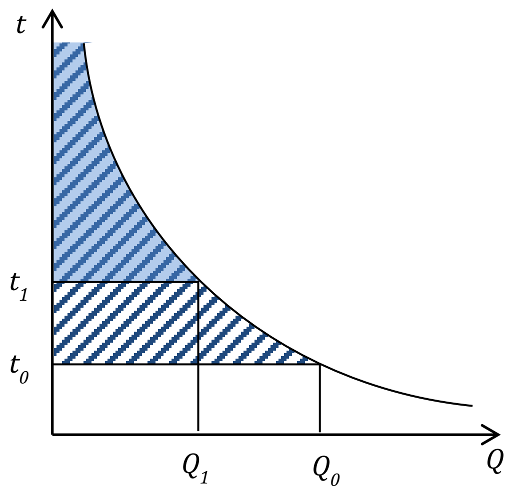

Figure 5.2. Change in consumer surplus with increase in travel time for a Cobb-Douglas demand function with *b* = -1

5.1 The Agency Perspective

As in the preceding analysis, we will continue to assume that the transit agency is constrained by an emissions budget. The revised optimization is as follows:

$$\text{Min } Z_{system} = Z_{user,T} + Z_{agency,T} \tag{5.4}$$

$$s.t.\ Z_{emissions,T} \leq E$$

In the figures below, the total system emissions ($Z_{emissions}$) are equal to the sum of the transit emissions ($Z_{emissions,T}$) and the marginal auto emissions due to users switching from transit to automobile travel ($Z_{emissions,A}$).

$$Z_{emissions,A} = \frac{L+W}{3} E_A D_A \tag{5.5}$$

where E_A is the emissions parameter for automobile travel in units of GHG emissions per kilometer and D_A is the demand for auto travel in units of passengers per hour. The first part of the term $\left(\frac{L+W}{3}\right)$ is the average travel distance for uniformly distributed origins and destinations. It is assumed that transit ridership is small enough so that automobile congestion is unaffected by the new drivers on the road. This would be the case in most US cities (McGuckin and Srinivasan 2003).

Figures 5.3 through 5.5 present the change in total GHG emissions as transit travel time is increased from the cost-optimal value for a range of travel time elasticities in scenario 2. The figures are each shown with the same scale on the X and Y-axes to allow for visual comparison.

The top line shows the results for an elasticity value of negative one, where users are most sensitive to changes in travel, and the bottom line shows the results for inelastic demand, where no users will change modes due to travel time increases. Since the purpose of any service reductions that increase travel time is to reduce emissions, the agency would want to be sure that it prevents too many users from switching to more polluting modes. In the case of bus (Figure 5.3), elasticity values of -0.8 through -1 produce a net increase in emissions over the travel time values shown, suggesting that slight service reductions for a city with highly elastic user demand would be detrimental to both the users and the environment. For an elasticity of -0.8 for bus, there is initially a small emissions benefit as the transit service is reduced, and this corresponds to the situation in Figure 5.1 where the emissions associated with area 3 are greater than the emissions associated with area 2. As the average transit travel time approaches 40 minutes, the curve enters the range where the emissions associated with area 2 are greater than the emissions associated with area 3, and there is a net emissions disbenefit associated with the service reductions. Elasticity values between 0 and -0.3 allow for reductions in emissions, and the remaining values cause moderate to no emissions reduction. This suggests that the small elasticity values may be appropriate for this scenario and mode, where headways are approximately 6 minutes at the cost-optimal point.

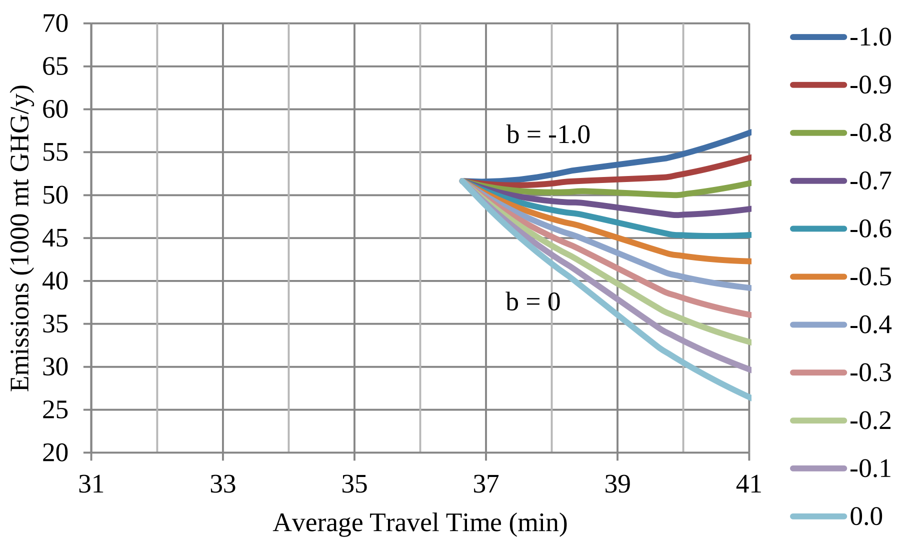

Figure 5.3. Change in emissions with travel time as level of service is reduced for bus

In the case of BRT (Figure 5.4), greater relative emissions reductions are possible, but the effects are moderated as the travel time increases. For example, with an elasticity value of -0.6, emissions hit a low at approximately 35.5 minutes and then begin to increase again. Returning to the mode comparison from the previous section, only elasticity values of 0 through -0.5 for BRT can produce an optimal system at the emissions level of 51,000 mt per year. The corresponding travel time varies between 33 minutes and 36 minutes, which means that BRT is still better than or competitive with LRT and bus for users with low to moderate elasticities. The emissions for

LRT (Figure 5.5) are more sensitive to reductions in user demand. Elasticity values of -0.6 through -1 all produce increases in emissions, so an LRT system should be designed near the cost-optimal point. Metro is not shown because it is not competitive with the other modes when access is restricted to walking. As shown in Sivakumaran et al. (2012), metro becomes more cost-effective with the addition of feeder bus service.

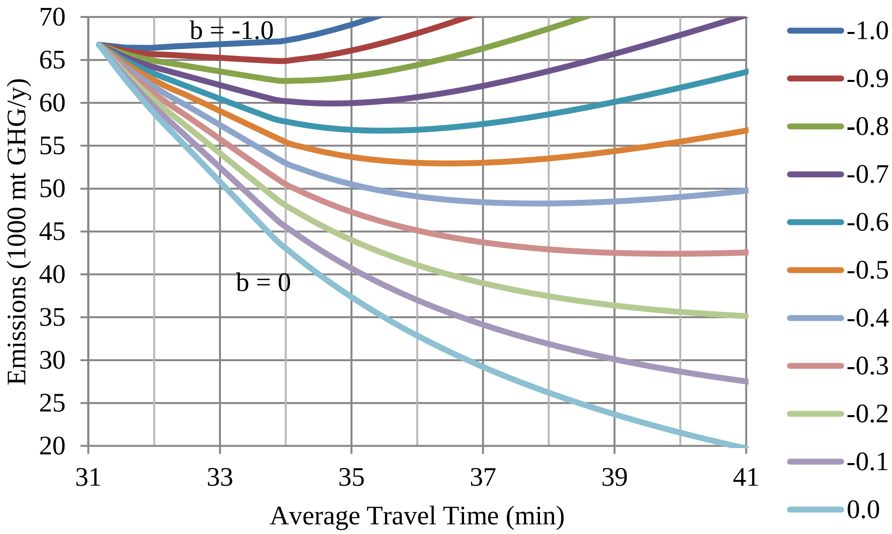

Figure 5.4. Change in emissions with travel time as level of service is reduced for BRT

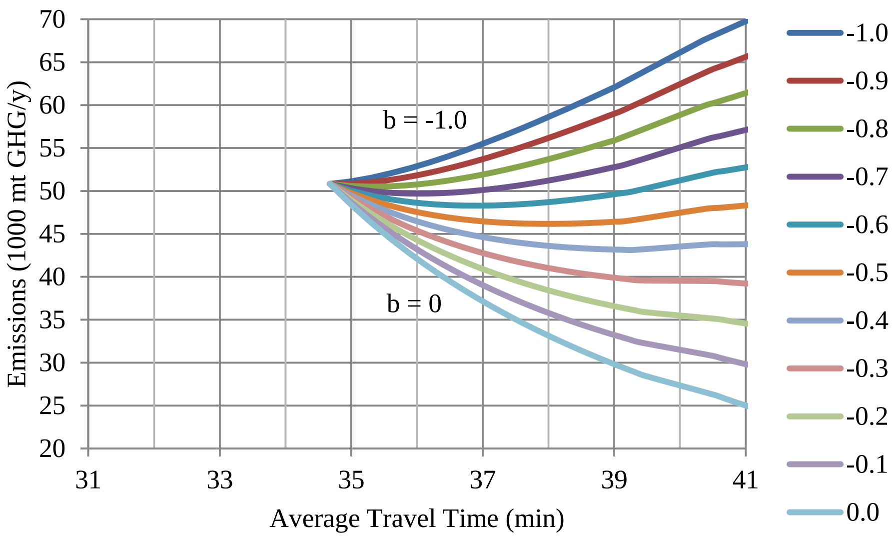

Figure 5.5. Change in emissions with travel time as level of service is reduced for LRT

Figures 5.3 through 5.5 show the tradeoff between travel time and emissions for different modes and elasticity levels. As demonstrated in Chapter 3, agency costs (Z_{agency}) decrease with emissions because the emissions reductions are implemented through reductions in service. One approach to retaining users could be to shift the agency cost savings back to users based on the travel time penalty that they suffer due to the reduction in service. The refund would be calculated as follows:

$$\frac{\Delta Z_{agency,T}}{D_{T'}} \times \frac{1}{t_o - t} \tag{5.6}$$

where TT_o is the cost optimal travel time. Figure 5.6 shows the potential per minute refund for users. Starting near the cost optimal, the refund is as high as \$0.33/min, or \$20/hr, the assumed wage rate for users in this city, but the refund reduces as the emissions are reduced further and the TT increases. For an elasticity value of 0.0, the line is otherwise straight because no users will switch to other modes and emissions will only reduce with level of service. For the other two elasticity values there is a smaller emissions-reduction payoff for the user incentive, and the lines curve back to the right as users shifting to other modes increase the automobile emissions enough to negate the benefits to transit.

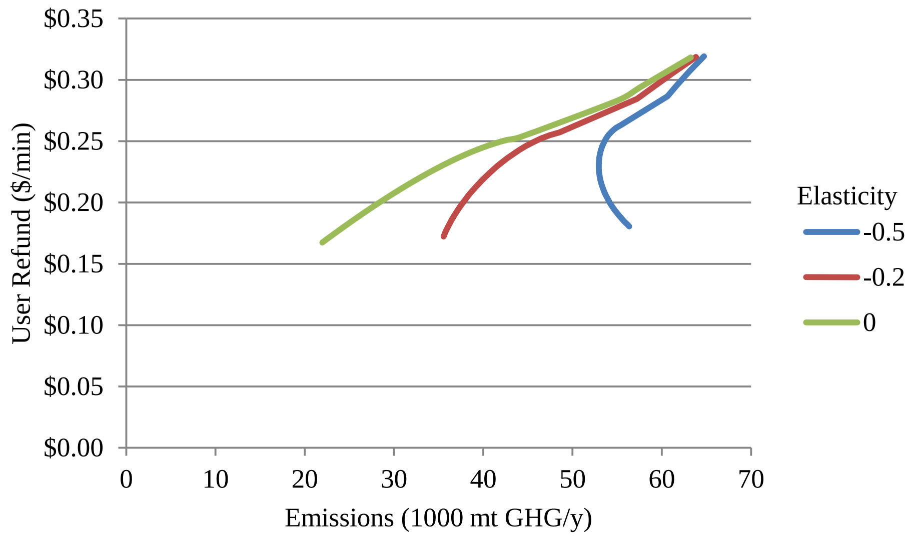

Figure 5.6. Potential user refund by emissions level for select elasticity values for BRT

5.2 The City Perspective

In the preceding section, the agency was constrained by an emissions budget, but as service was reduced to accommodate the emissions reductions, users switched to automobile and the net emissions increased for some elasticity values. Under California's Assembly Bill 32 (AB 32), agencies will similarly have emissions budgets imposed on them by the state. When such an agency-specific approach is taken, the mitigation efforts can backfire, as was shown. A more holistic approach would be to look at the problem from the perspective of the city, rather than just the agency. In this case, the emissions from other modes are included in the budget so that the optimization captures the effect of user mode shift:

$$\text{Min } Z_{system} = Z_{user,T} + Z_{agency,T} \tag{5.7}$$

$$s.t.\ Z_{emissions,T} + Z_{emissions,A} \leq E$$

The results for this optimization for bus, BRT, and LRT in scenario 2 are shown in Figures 5.7, 5.8, and 5.9 respectively. Including the marginal automobile emissions in the emissions constraint means that the emissions will never increase as the transit travel time increases. The curves are very similar to the corresponding ones for the agency perspective, except that they do not exhibit an increase in emissions. There is only so much an agency can do to reduce emissions through the operational approaches before enough users will shift modes and negate the efforts. For transit systems with more elastic users, there is a smaller scale of possible emissions reductions as well as a smaller increase in travel time for users. For bus and BRT, the line for *b* = -1.0 is hidden behind the other curves, and the changes in emissions and travel time are negligible. For LRT, there are not possible emissions reductions for values of *b* from -0.8 through -1.0. This result is consistent with the upward curves for the same values for LRT in the agency perspective.

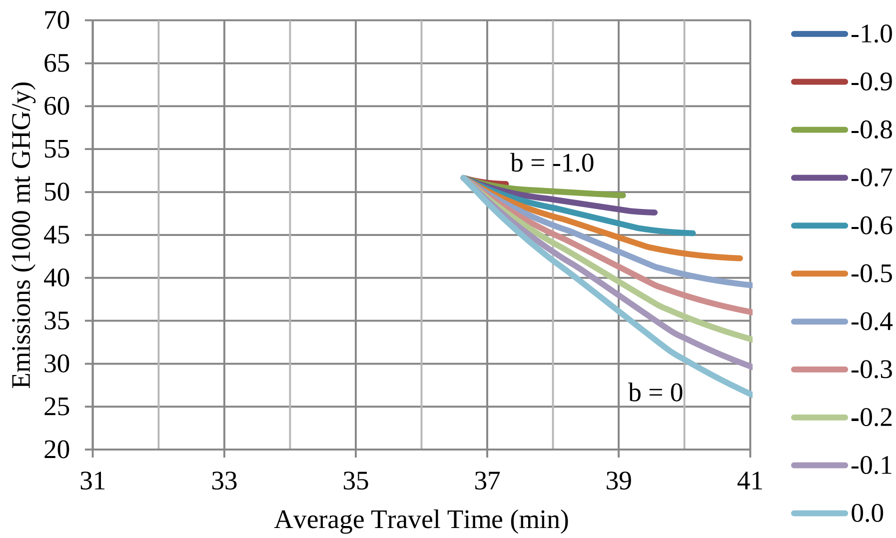

Figure 5.7. Change in emissions with travel time as level of service is reduced for bus from city perspective

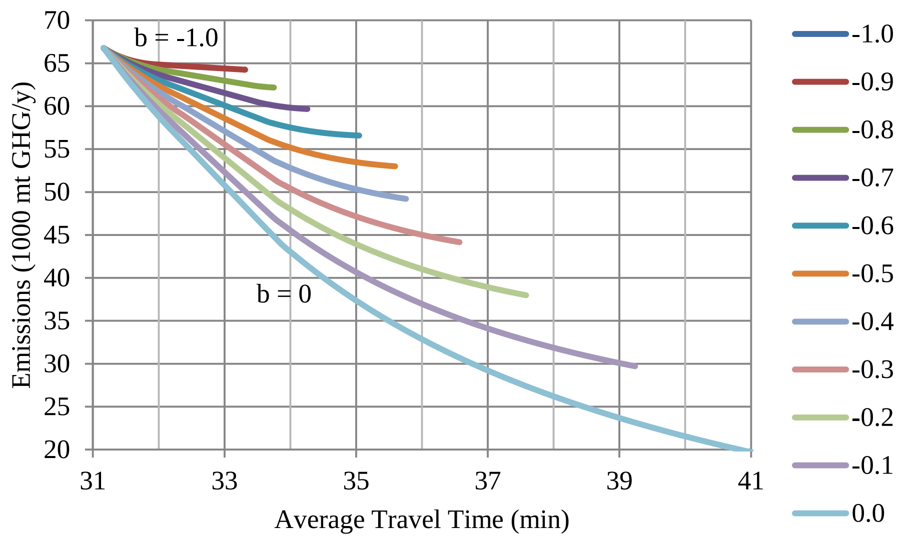

Figure 5.8. Change in emissions with travel time as level of service is reduced for BRT from city perspective

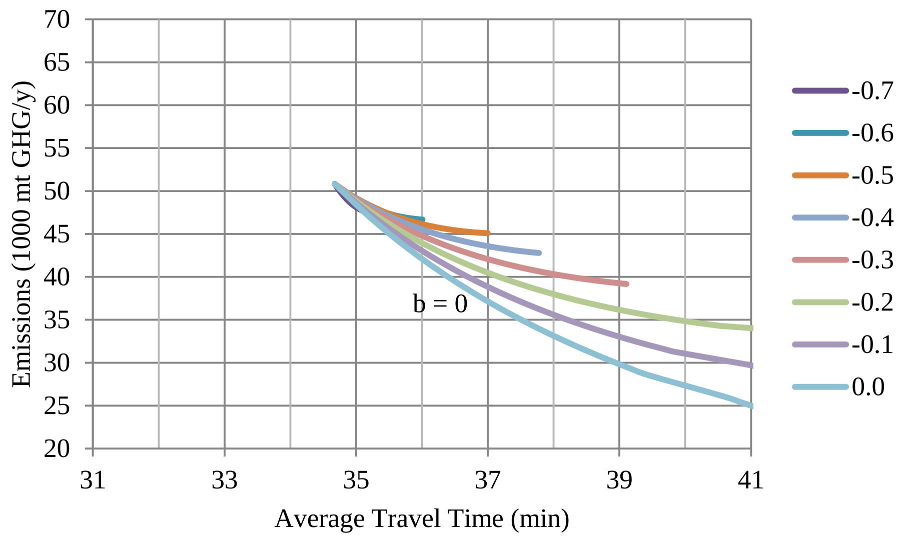

Figure 5.9. Change in emissions with travel time as level of service is reduced for LRT from city perspective

These results show that there may be disadvantages to regulatory approaches that impose GHG emission reduction targets on individual agencies, because they do not take into account the unintended consequences that result from agencies focusing solely on their energy savings. This analysis also shows that approaches that have an urban, metropolitan or regional scope are likely to produce better results. This city perspective could help to improve the implementation of laws like AB 32 and avoid unintended consequences when emissions are shifted to other modes.

Chapter 6. Sensitivity Analysis & Uncertainty

6.1 Sensitivity Analysis

The carbon price analysis demonstrates that small changes in the values of the decision variables have a very small effect on the optimal cost, but a larger effect on the optimal emissions. To further examine this behavior of the model, I performed sensitivity analysis on the emissions parameters for each mode in scenarios 2 and 3. Increasing or decreasing each parameter by 50 percent caused small changes in the optimal cost results and produced the cost-optimal GHG emissions shown in Tables 6.1 and 6.2. For all the modes except metro, altering the vehicle operations parameter (E_V) was the only change to cause greater than 3% changes in the total emissions at the cost-optimal point. The changes for metro were larger (up to 14%) for the two infrastructure parameters (E_I, E_S). For scenario 2, metro was more sensitive to changes in E_s than for scenario 3, and the inverse was true for E_I. Scenario 3 is a large city with greater stop spacing, so it makes sense that the relative impact of ROW infrastructure would increase.

Table 6.1. Sensitivity analysis on emissions parameters for cost-optimal emissions for scenario 2

Parameter	Pct. Change	GHG (1000 mt/yr) Bus	BRT	LRT	Metro
base case		52	66	51	261
E_I	+50%	52	67	51	275
E_I	−50%	52	65	51	246
E_V	+50%	77	98	75	340
E_V	−50%	26	33	27	181
E_S	+50%	52	68	52	298
E_S	−50%	52	66	51	224

Table 6.2. Sensitivity analysis on emissions parameters for cost-optimal emissions for scenario 3

Parameter	Pct. Change	GHG (1000 mt/yr) Bus	BRT	LRT	Metro
base case		325	423	312	1630
E_I	+50%	325	424	315	1758
E_I	−50%	325	422	310	1504
E_V	+50%	487	628	462	2129
E_V	−50%	163	219	163	1132
E_S	+50%	326	430	317	1821
E_S	−50%	325	417	308	1441

Although the optimal costs do not change with the sensitivity analysis, the emissions change with variation in E_V and cause significant changes to the shape of the Pareto curve (Figure 6.1). This result suggests that improved bus technology, such as natural gas vehicles, could significantly improve the emissions for both bus and BRT. Additionally, the operating emissions for LRT and metro are highly dependent on the electricity mix, which is the California mix for the parameters used here. A transit system in Seattle, Washington would have lower operating emissions because of the large percentage of electricity coming from hydroelectric power. In Cleveland, Ohio, on the other hand, the electricity mix is more heavily dependent on coal power, so operating emissions would be significantly higher. Examining the source of the emissions for each mode (Table 6.3), one can see that infrastructure is the source of 30 percent of the emissions for metro, and no more than 4.5 percent for the other modes. This result further emphasizes the importance of vehicle technology and electricity mix for reducing transit emissions.

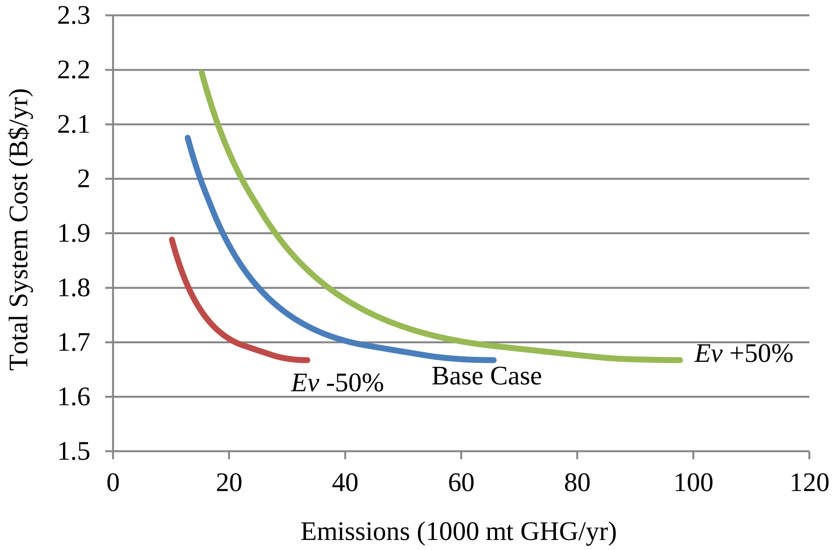

Figure 6.1. Sensitivity analysis on E_V for BRT in scenario 2

Table 6.3. Source of cost-optimal emissions by mode for scenario 2

	Total	Operating and Fleet	ROW Infrastructure	Station Infrastructure
Bus	0.61	99%	0.02%	0.5%
BRT	0.52	98%	0.3%	1.8%
LRT	0.58	95%	1.2%	3.3%
Metro	0.61	71%	13%	17%

6.2 Emissions

The emissions results are uncertain, as demonstrated by the sensitivity analysis. The final emissions can vary by as much as 50 percent within reasonable ranges of vehicle operations parameter values (Table 6.2). These parameters are based on outputs from Chester and Horvath (2009), who assessed them as being of relatively good quality. They based bus operating emissions, however, on a standard drive cycle, which cannot account for the nuance in the actual model drive cycle as the stop spacing varies. The BRT vehicle manufacturing and operating emissions are prorated from standard diesel bus emissions, and are therefore, less accurate. Infrastructure emissions are less certain than the vehicle emissions as they are based on U.S. industry averages from EIO-LCA (CMU 2008) and do not account for local variations. The infrastructure emissions also have a much smaller impact on the total emissions, so variation in the parameter values will have a proportionately smaller impact.

6.3 Travel Time

The travel time estimates are also uncertain. They are based on assumed average speeds of vehicles while they are running and assumed lost time for stops and transfers (Table 2). The commercial speed is dependent on the cruising speed of the vehicle, the number of stations where vehicles must stop, and for bus, the speed of surrounding vehicle traffic and the number of stop signs and signals on the route. The lost time is dependent on the level of demand at each stop and the coordination of route scheduling. Bus travel times are the most prone to fluctuation because the vehicles must mix with traffic, but the other travel times are not deterministic either.

6.4 Costs

I am most confident in the cost estimates as they are based on actually costs or estimates for construction of San Francisco Bay Area transit systems. Wage rates and construction costs will vary in other parts of the country. The costs for metro construction assume a mix of surface, underground, and aerial tracks and stations that will be different for other cities.

Chapter 8. Conclusion

This dissertation presents an approach to assessing the tradeoffs between costs and GHG emissions in the design of urban transit systems. Using continuum approximation models, I optimize urban transit systems for costs at different emissions constraints, and obtain Pareto frontiers of optimal transit system design. Parametric analysis of different city scenarios allows for comparison of the optimal system attributes for each mode in different types of cities. Additionally, the Pareto curves aid in the evaluation of the system changes and user impact of GHG reductions. Results of the parametric analysis suggest that a BRT system is a low cost and low emissions transit option for many types of cities. The lowest cost mode also has the lowest travel time, so in the scenarios examined here, BRT is the best mode choice. In addition, implementing small emissions reductions from the cost-optimal level with these models may not be practical; a city has limited flexibility for minute changes in route or stop spacing when fitting them onto an establish grid street network.

Choosing GHG reduction levels based on the market price of carbon has a small impact on user travel time. Incorporating travel time elasticities into the model formulation, one can estimate the emissions impact of reductions in level of service. Some users will switch to driving when the transit travel times become intolerable. For travel time elasticites values between 0.0 and -0.5, the reductions in service will allow for some emissions reductions, despite the new drivers on the road. Bus and BRT allow for greater emissions reduction than LRT for these low to moderately inelastic users. For elasticity values between -0.5 and -1.0, there is a small to negative emissions benefit to any service reductions. When looking at the problem from the city or regional perspective, by including the marginal automobile emissions in the constraint, the results are limited to the range that will produce net emissions reductions, clarifying the solution for both the agency and policymakers.

It is important to remember that the GHG emissions reductions analyzed here are relative to those at the cost-optimal point. However, many existing transit systems may be operating at both higher cost and emissions outside the Pareto frontier, so a shift to the cost-optimal point would already represent significant emissions reductions. In a national survey of transit agencies, Saka (2003) found the average bus stop spacing to be 330 meters. This is sub-optimal for both users—many stops increase the in-vehicle travel time—and agencies—increasing the cycle time per vehicle, and thus, the number of vehicles needed to maintain headways. The cost-optimal spacing for bus was between 0.8 kilometers and 1.6 kilometers for the scenarios examined here. Many existing bus systems could potentially see considerable reductions in costs and emissions by optimizing their system for costs only. Additionally, some transit riders are captive users who have no other transportation options, so it is important to balance transit emissions reductions with policies targeted at other modes.

The approaches described here could be used to optimize the network design of existing bus service or help to select the mode and design attributes for a new transit system. Transit agencies can estimate the cost of GHG emissions reductions and identify the scale of reasonable reductions.

8.1 Future Work

This study is limited to single-mode transit systems with walking access, but relative benefits of the trunk modes are expected to change when faster feeder modes are included (Sivakumaran et al. 2012). Consideration of feeder modes, including bus, bike, and auto, could make the analysis more realistic. Additionally, it may be worthwhile to examine other demand patterns, including many-to-one for cities with a central business district or other non-uniform spatial and temporal patterns. The results reflect a single technology for each mode (i.e., diesel for bus), and consideration of other vehicle technologies may change the results. For instance, the emissions parameters for metro are based on the BART system, which uses 50-year-old technology and has very long trains, and thus, longer platforms that require extra infrastructure than other systems might. This analysis does not account for the size or capacity of the transit vehicle, and future work would benefit from inclusion of capacity constraints or variable train length. The models defined here are for a transit system with a grid network, but one could also develop models for systems with other designs, such as radial or ring-radial, which may favor different modes.

GHGs are global air pollutants, but other local pollutants that were not considered in the analysis can have an effect on the health of the transit users and the local population. In the case of local pollutants, the location where the emissions are produced has a great effect on the impacts to society. Future work could include the criteria air pollutants to see the impact on the favorability of the electric powered modes over diesel.

These approaches are intended to be used in the initial, strategic design stages. Before applying these models, transit planners should be sure to have good estimates of the level of transit demand for the particular urban area to avoid over- or under-designing the system.

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Appendix A – Derivation of Cost Parameters

Bus Costs

Parameter	Value	Comments
C_I – ROW Infrastructure cost		
Amortized cost ($/km-hr)	**$10**	From Sivakumaran (2012). Based on assumed lifetime estimate of 20 years
C_S – Station infrastructure cost		
Total cost ($/st-hr)	**$0.82**	10% of BRT
C_V – Vehicle purchase, fuel & maintenance cost		
Vehicle lifespan (miles)	500,000	Chester (2008)
Vehicle purchase price ($)	$330,000	40-ft Van Hool bus purchase by AC Transit in 2007 (Gammon 2008) converted to 2012 dollars
Amortized vehicle price ($/veh-km)	$0.41	
Maintenance cost ($/veh-km)	$0.22	$0.20 from Clark et al. (2007) converted to 2012 dollars
Diesel fuel price ($/gal)	$4	US EIA (2012)
Fuel efficiency (mpg)	6	Clark et al. (2007)
Fuel cost ($/veh-mi)	$0.67	
Fuel cost ($/veh-mi)	$0.41	
Total cost ($/veh-km)	**$1.0**	
C_M – Labor Cost		
# Employees per vehicle	3	From Wilson (2010) and Pushkarev & Zupan (1972)
Average wage ($/hr)	$20	
Wage cost ($/veh-hr)	$60	
Labor cost ($/veh-hr)	**$150**	Including agency cost markup

BRT Costs

Parameter	Value	Comments
C_I – ROW Infrastructure cost		
Planning horizon (years)	40	
ROW costs ($)	$132.1 million	Converted to 2012 from budget estimate for Geary Blvd BRT project (SFCTA 2007)
Project length (km)	10.5	
Cost per km ($/km)	$12.6 million	
Amortized cost ($/km-hr)	**$36**	
C_S – Station infrastructure cost		
Planning horizon (years)	40	
Stop costs ($)	$34.3 million	Converted to 2012 from budget estimate for Geary Blvd BRT project (SFCTA 2007)
Number of stops	12	
Cost per stop ($/stop)	$2.86 million	
Amortized cost ($/st-hr)	**$8.2**	
C_V – Vehicle purchase, fuel & maintenance cost		
Vehicle lifespan (miles)	500,000	Chester (2008)
Vehicle purchase price ($)	$590,000	60-ft articulated Van Hool bus purchase by AC Transit in 2007 (Gammon 2008) converted to 2012 dollars
Amortized vehicle price ($/veh-km)	$1.17	
Maintenance cost ($/veh-km)	$0.33	$0.20 from Clark et al. (2007) prorated for larger vehicle and converted to 2012 dollars
Diesel fuel price ($/gal)	$4	USEIA (2012)
Fuel efficiency (mpg)	4.62	Clark et al. (2007) prorated for relative difference in consumption (Zargari & Kahn 2010)
Fuel cost ($/veh-mi)	$0.87	
Fuel cost ($/veh-km)	$0.54	
Total cost ($/veh-km)	**$1.6**	
C_M – Labor Cost		
# Employees per vehicle	4	From Wilson (2010) and Pushkarev & Zupan (1972)
Average wage ($/hr)	$20	
Wage cost ($/veh-hr)	$80	
Labor cost ($/veh-hr)	**$200**	Including agency cost markup

LRT Costs

Parameter	Value	Comments
C_I – ROW Infrastructure cost		
Planning horizon (years)	40	
Project cost ($)	$717 million	Converted to 2012 from costs for Muni T-third light rail line (SFMTA 2012)
ROW costs ($)	$645 million	Assume 90% of costs go to ROW
Project length (km)	8.2	
Cost per km ($/km)	$78.6 million	
Amortized cost ($/km-hr)	**$220**	
C_S – Station infrastructure cost		
Planning horizon (years)	40	
Station costs ($)	$71.7 million	Assume 10% of Muni T-third budget
Number of stations	18	
Cost per station ($/station)	$3.98 million	
Amortized cost ($/st-hr)	**$11**	
C_V – Vehicle purchase, fuel & maintenance cost		
Useful life (years)	27	Chester (2008)
Annual vehicle revenue miles (miles/year)	12,000	MTC (2012)
Lifetime mileage (miles)	324,000	
Vehicle purchase price ($/veh)	$2.92 million	$2 million price (Nolte 1996) converted to 2012 dollars
Amortized vehicle price ($/veh-km)	$5.61	
Energy use of veh (kWh/veh-km)	4.4	Chester & Horvath (2009)
Cost per kWh ($/kWh)	$0.1	US EIA (2012)
Operating cost ($/veh-km)	$0.44	
Total cost ($/veh-km)	**$6.0**	
C_M – Labor Cost		
# Employees per vehicle	4	From Wilson (2010) and Pushkarev & Zupan (1972)
Average wage ($/hr)	$20	
Wage cost ($/veh-hr)	$80	
Labor cost ($/veh-hr)	**$200**	Including agency cost markup

Metro Costs

Parameter	Value	Comments
C_I – ROW Infrastructure cost		
Planning horizon (years)	40	
Project cost ($)	$1.82 billion	Converted to 2012 from costs for BART SF airport extension (FTA 2005)
ROW costs ($)	$1.64 billion	Assume 90% of costs go to ROW
System length (km)	17.7	
Cost per km ($/km)	$92.6 million	
Amortized cost ($/km-hr)	**$260**	
C_S – Station infrastructure cost		
Planning horizon (years)	40	
Station costs ($)	$71.7 million	Assume 10% of SF airport extension
Number of stations	4	
Cost per station ($/station)	$45.5 million	
Amortized cost ($/st-hr)	**$130**	
C_V – Vehicle purchase, fuel & maintenance cost		
Useful life (years)	40	Chester (2008)
Annual vehicle revenue miles (miles/year)	66,000	MTC (2012)
Lifetime mileage (miles)	2,640,000	
Vehicle purchase price ($/veh)	$2.92 million	Average 8.4 cars per train (Chester 2008); Contract price for new BART cars (BART 2012)
Amortized vehicle price ($/veh-km)	$4.32	
Energy use of veh (kWh/veh-km)	46	Chester & Horvath (2009)
Cost per kWh ($/kWh)	$0.1	US EIA (2012)
Operating cost ($/veh-km)	$4.6	
Total cost ($/veh-km)	**$8.9**	
C_M – Labor Cost		
# Employees per vehicle	5	From Wilson (2010) and Pushkarev & Zupan (1972)
Average wage ($/hr)	$20	
Wage cost ($/veh-hr)	$100	
Labor cost ($/veh-hr)	**$250**	Including agency cost markup

Appendix B – Derivation of Emissions Parameters

Bus Emissions

Parameter	Value	Comments
E_I – ROW infrastructure emissions		
Amortized ROW emissions (g/km-hr)	**8.1**	5% of BRT because ROW is shared with cars and trucks
E_S – Station infrastructure emissions		
Station emissions (g/st-hr)	**1,700**	10% of BRT
E_V – Operating and fleet emissions		
Vehicle lifespan (miles)	500,000	Chester (2008)
Vehicle manufacturing emissions (mt/veh)	129	Standard diesel bus (Chester & Horvath 2009)
Amortized vehicle manufacturing (g/veh-mi)	258	
Operation emissions (g/veh-mi)	2,400	Chester & Horvath (2009)
Maintenance emissions (g/veh-mi)	45	Chester & Horvath (2009)
Total emissions (g/veh-mi)	2,703	
Total emissions (g/veh-km)	**1,700**	

BRT Emissions

Parameter	Value	Comments
E_I – ROW infrastructure emissions		
Lifetime (years)	20	
GHG emissions for pavement maintenance (g/ft^2)	614	Chester (2008)
Width of ROW (ft)	14	
ROW emissions (mt/km)	28.2	
Amortized ROW emissions (g/km-hr)	**160**	
E_S – Station infrastructure emissions		
Station emissions (g/st-hr)	**1,700**	Same as LRT
E_V – Operating and fleet emissions		
Vehicle lifespan (miles)	500,000	Chester (2008)
Vehicle manufacturing emissions (mt/veh)	194	Prorated 150% from standard diesel bus (Chester & Horvath 2009)
Amortized vehicle manufacturing (g/veh-mi)	387	
Operation emissions (g/veh-mi)	3,120	Prorated 130% Chester & Horvath (2009) diesel bus (Zargari & Kahn 2010)
Maintenance emissions (g/veh-mi)	45	Chester & Horvath (2009)
Total emissions (g/veh-mi)	2, ,552	
Total emissions (g/veh-km)	**2,200**	

LRT Emissions

Parameter	Value	Comments
E_I – ROW infrastructure emissions		
Planning horizon (years)	40	
GHG emissions per km (mt/km)	277	Based on materials used for Muni Metro system from Chester (2008) and EIO-LCA (CMU 2012)
Amortized ROW emissions (g/km-hr)	**790**	
E_S – Station infrastructure emissions		
Planning horizon (years)	40	
Station construction emissions (mt/station)	603	Other dimensions and concrete requirements based Muni Metro system from Chester (2008); emissions from EIO-LCA (CMU 2012)
Station emissions (g/st-hr)	**1,700**	
E_V – Operating and fleet emissions		
Vehicle lifespan (miles)	324,000	
Vehicle manufacturing emissions (mt/veh)	338	Muni Metro LRT vehicle (Chester & Horvath 2009)
Amortized vehicle manufacturing (g/veh-mi)	1,043	
Operation emissions (g/veh-mi)	2,800	Chester & Horvath (2009)
Maintenance emissions (g/veh-mi)	500	Chester & Horvath (2009)
Total emissions (g/veh-mi)	4,343	
Total emissions (g/veh-km)	2,700	

Metro Emissions

Parameter	Value	Comments
E_I – ROW infrastructure emissions		
Planning horizon (years)	40	
GHG emissions per km (mt/km)	15,300	Based on materials used for BART system from Chester (2008) and EIO-LCA (CMU 2012)
Amortized ROW emissions (g/km-hr)	**11,000**	
E_S – Station infrastructure emissions		
Planning horizon (years)	40	
Station construction emissions (mt)	41,100	Other dimensions and concrete requirements based Muni Metro system from Chester (2008); emissions from EIO-LCA (CMU 2012)
Station emissions (g/st-hr)	**120,000**	
E_V – Operating and fleet emissions		
Vehicle lifespan (miles)	2,640,000	
Vehicle manufacturing emissions (mt/veh)	1,841	BART train (Chester & Horvath 2009)
Amortized vehicle manufacturing (g/veh-mi)	697	
Operation emissions (g/veh-mi)	16,000	Chester & Horvath (2009)
Maintenance emissions (g/veh-mi)	427	Chester & Horvath (2009)
Total emissions (g/veh-mi)	17,120	
Total emissions (g/veh-km)	**11,000**	